Trust in Finance and Consumer Fintech Adoption*

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Abstract

We study the impact of trust in traditional finance on the consumer adoption of various fintech products, including cryptocurrencies, peer-to-peer lending, other crowdfunding, roboadvisors, and alternative payment solutions. Using a representative survey of Dutch households, an online lab experiment and an experiment on an investment website, we find no consistent evidence that trust in finance affects fintech adoption in any product category (though we find weak evidence showing that trust in finance positively affects interest in alternative payment apps). Our results suggest that consumers consider fintech products to be distinct from traditional financial products.

JEL classification: D14, G23, G41, G50

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1 Introduction

An erosion of trust in the traditional financial system has been commonly proposed as an explanation for the substantial increase in fintech usage after the financial crisis of 2008. This narrative argues that a lack of trust in traditional finance has led consumers to seek alternatives, with technology-oriented companies and entrepreneurs providing them.[1] Although the narrative of distrust in traditional finance driving fintech adoption is compelling, an observed correlation between these two variables doesn't necessarily imply causality. For example, the rapid increase in fintech lending could be due to faster processing times, lower operational costs, and improvements in screening provided by the recent advances in technology (Berg, Fuster, and Puri (2022)).

Fintech is also a very broad term that encompasses many products. Some products, such as many cryptocurrencies, are generally associated with mistrust in the financial system and institutions in general. Other products, such as alternative payment apps (like Venmo) are seen as complements to traditional finance. Existing empirical work (Saiedi, Mohammadi, Broström, and Shafi (2020); Yang (2021) and Bertsch, Hull, Qi, and Zhang (2020)) that provides some evidence of distrust in traditional finance driving fintech adoption is limited to a single class of fintech products, peer-to-peer borrowing.

In this paper, we study the impact of trust in traditional finance on the adoption of various fintech products, using a combination of survey-based and experimental methods. We focus on four categories of financial products, which cover a significant portion of consumer fintech usage in developed economies: cryptocurrencies, roboadvisors, peer-to-peer lending, and non-bank payment systems. Our survey is a large-scale representative survey of households in the Netherlands which allows us to study the cross-sectional association between trust in finance and consumer fintech adoption while controlling for a wide range of covariates. We also conduct two experiments to avoid the usual omitted variable problems associated with

[1] See, for example, Goldstein, Jiang, and Karolyi (2019) and Yermack (2015) on the academic side and Rooney (May 2, 2019) and Rooney (September 14, 2018) on the media.

observational data. The first uses Prolific, a tool for online experiments, to make distrust in finance more salient for randomly selected participants. In the second experiment, we commission articles on a popular Finnish investment website on topics that may stir distrust in finance. Within these articles and a set of "control" articles, we embed randomized links to articles on fintech and traditional finance-topics and measure clickthrough rates to these articles.

Our results are surprising. Contrary to common narrative, we find no consistent relationship between adoption of any of the fintech products and trust in finance. In the survey there is no positive association between trust and any of fintech products except payment apps. In experiments, individuals who are primed to distrust traditional finance show similar levels of interest towards fintech products as an unprimed control group, other than perhaps alternative payment apps (though the result is statistically insignificant). Overall, our results suggest that people do not consider fintech products to be "finance" but rather something different.

None of these methods (which we describe in more detail later) is perfect. There is considerable potential for omitted variable bias in our survey approach as we may not be able to control for all potential variables affecting both trust and use of fintech. In the Prolific experiment, we have perfect randomization but there are legitimate concerns about a lack of power. The experiment on the website suffers from an obvious selection bias. Across all of our settings, the worry that our trust measure does not accurately describe true levels of trust is present – although we show that our measure does have power in predicting things such as stock market participation in both the survey and first experiment.[2] Despite all of these concerns, the general consistency of our results across different settings suggests that the traditional narrative on trust and the rise of fintech should be approached with some caution. An alternative explanation to our results would need to explain both why we do not observe any relationship in empirical settings which are designed to compensate for the flaws

[2]The second experiment is designed in a way where the unconditional relationship between trust in finance and usage of traditional financial products cannot be tested.

of the other settings we use. Our results do not imply that trust does not matter for fintech adoption but rather that, in our sample of people living in developed countries (US, UK, Finland and the Netherlands), consumers might not view fintech products as substitutes to traditional financial products.

Our observational (survey) approach uses the Longitudinal Internet Studies for the Social Sciences (LISS) panel, a rich panel survey of a representative sample of households in the Netherlands. This survey is administered on a monthly basis to about 5,000 households in the Netherlands, consisting of rotating core waves of questions as well as additional questions added onto the survey by researchers. We add questions to the September 2019 and August 2020 waves of the survey.

In order to elicit trust in finance, we ask participants in the LISS panel "In general, do you think banks can be trusted?" (the answer is given on a 10-point scale). We use this wording (instead of "How much do you trust banks" as in the Sapienza and Zingales' Financial Trust Index) to maintain consistency with other questions on trust in the LISS panel. We also ask questions on participants' interest in various fintech products. These questions provide us with cross-sectional measures of both trust in finance and fintech adoption, and we repeat them across two waves (2019 and 2020).[3] The richness of the LISS panel allows us to control for a range of background variables, including demographics, income, financial literacy, ambiguity aversion and other factors that might otherwise confound our results.

In the survey, we find that higher trust in finance is positively associated with reported use of alternative payment solutions and the number of fintech apps on one's mobile phone and weakly negatively associated with the use of cryptocurrencies.[4] We find no significant relationship between trust in finance and the use of P2P lending platforms. This last result seems to contradict the findings of Bertsch et al. (2020) and Saiedi et al. (2020), though we discuss the differences between our results and theirs. Our results are robust to controlling

[3] In the end, the differences between the two waves are small and our results are essentially cross-sectional.

[4] Most of the fintech payment apps mentioned in the previous analysis are payment platforms and these are mostly associated with banks.

for age, gender, education, occupation, income, political and societal views, financial literacy, and risk aversion, among other things. The positive correlation between trust in finance and interest in alternative payment systems is in contrast to our experimental results, described below. We hypothesize that this may be driven by the fact that almost all payment apps and systems in the Netherlands are strongly associated with and promoted by banks, even when they are not directly owned by any one bank (several are owned by consortia of banks, for instance).

One obvious concern may be that our trust measure is not valid. For example, it may be driven by people simply randomly clicking on a number in a survey in a way that does not reflect their "true" level of trust in finance. To validate our measure of trust in finance, we also show that trust in banks is significantly positively associated with holdings of risky investments, consistent with the results of Guiso, Sapienza, and Zingales (2008). Guiso et al. (2008) show that stock market participation and risky asset share are positively related to trust in finance, a result that we are able to replicate in our sample. This suggests that our measure of trust is valid insofar that it is consistent with prior literature, and that consumers view fintech products as being distinct from other risky assets such as shares and mutual funds.

Since trust in finance may be correlated with some background variable that we are unable to observe, we also conduct an experiment in which we temporarily prime randomly selected participants to distrust financial institutions. This experiment is conducted on Prolific. The idea behind the experiment, described in more detail in Section 4.1, is to prime distrust in traditional finance in participants in the experiment.[5] We do this by asking them questions about negative experiences in life, first with two innocent questions that are the same for everyone and then either a priming or control question (randomized by participant), related to either bad experiences with financial institutions / banks (treatment group) or other firms

[5]Priming is a frequently used method not only in psychology but more recently also in finance and economics. For recent examples, see, e.g., Cohn, Fehr, and Maréchal (2014); Cohn, Engelmann, Fehr, and Maréchal (2015), Callen, Isaqzadeh, Long, and Sprenger (2014), or D'Acunto (2019a,b).

(control group). We then ask participants about their level of trust in finance and find that it is significantly lower in the treatment group than in the control group, suggesting that our priming does indeed lower trust levels. Finally, we ask participants about their interest in various fintech products. In this experiment, we observe close to no differences between the treated and control groups in almost any product category, despite apparently successfully priming the trust levels. [6]. We do acknowledge that our experiment may be underpowered in the sense that it does not induce significant differences in trust in finance, but think that *interpreted in conjunction with our other results*, the case for a limited effect of trust in finance on fintech usage in a context where customers do not consider the two substitutes.

As with the survey, we attempt to validate our measure by testing whether our treatment (priming) affects interest in traditional financial products. We present two results to support the idea that our treatment indeed lowers trust in finance: First, we report that participants in the treated group report lower levels of trust in finance but not lower levels of trust in people (though the effect is not huge). Second, we show that people in the treated group report lower interest in stocks than those in the control group, though this difference is not statistically significant. We also show that unconditionally, our trust in finance measure is positively associated with interest in stocks and mutual funds.[7]

One potential drawback of this experiment is experimenter demand effects (*i.e.,* subjects understand that they are being experimented on and as such may adjust their behavior). This is particularly important in our context, when respondents were offered bonuses to incentivize thoughtful answers and effort. While our pilot studies (where we explicitly asked participants to guess the purpose of the experiment and offered significant bonuses for doing so) showed that only about 10% of participants understood that we were attempting to stir distrust in finance, it is still important to address this concern.

In order to do so, we conduct an experiment on a Finnish investment website with over

[6] We also show that reported levels of trust (*i.e.,* not changes induced by the experiment but unconditional levels) are positively associated with interest in traditional financial products.

[7] However, as we do not have detailed demographic data, we are unable to control for potential confounders such as age.

250,000 monthly readers. We work with the website to write articles on topics designed to stir distrust in finance (such as stories about banks paying compensation to customers for mis-selling financial products), which we call treatment articles, and pair these with control articles chosen randomly from articles published the same day.[8] In these articles we embed (randomized) links to existing articles on fintech products (for example "Bitcoin as a part of your investment portfolio") and traditional financial products. [9] We then track clicks to the fintech and non-fintech articles from both classes of articles and observe no major differences between click rates in the fintech and non-fintech product categories.

In sum, we use a range of methods, a large-scale survey and multiple experiments, to find the association between trust in traditional finance and fintech adoption. It was just not there. Our results suggest that trust in traditional finance is not an important driver of fintech adoption, and possibly that prior studies should be interpreted with some caution. Overall our findings are consistent with the idea that consumers do not view common fintech products as being financial products but instead of as something unrelated.

2 Relevant literature

There is considerable evidence that trust (and trust in finance) affects for instance stock market participation and use of traditional financial services (see, e.g., Guiso, Sapienza, and Zingales, 2004; Guiso et al., 2008; Allen, Demirguc-Kunt, Klapper, and Peria, 2016; Dupont and Karpoff, 2020; Andersen, Hanspal, and Nielsen, 2019). Thakor and Merton (2018) develop a theoretical model of the role of trust in the competition between banks and non-bank lenders, focusing on institution-specific trust, arguing that banks have stronger incentives to maintain trust than non-bank lenders. Armantier, Doerr, Frost, Fuster, and Shue (2021) document differences in households' trust to safeguard their personal data in

[8]We began this experiment by pairing the first two articles with one matched control article that matched the theme and format of the existing article, but changed this. See the data and methodology section.

[9]We could not find a suitable existing article on payment apps nor an equivalent non-fintech article, so we discarded this category from the experiment.

different types of financial intermediaries (*e.g.,* banks and fintech companies). However, it is not clear whether trust in traditional financial institutions correlates positively or negatively with fintech adoption, and whether there are differences across different fintech products. It is plausible that this depends on whether consumers consider fintech products to be substitutes or complements to traditional financial products.

We focus on the consumer adoption of four different categories of fintech products: cryptocurrencies, roboadvisors, peer-to-peer lending/borrowing and non-bank payment systems. While the rise of Bitcoin and other cryptocurrencies has generated a vast amount of attention and public discussion, studying cryptocurrency adoption and its drivers remains challenging given the typically semi-anonymous nature of cryptocurrency transactions and, therefore, the lack of data on the users. Anecdotal and survey-based evidence suggests that there are several distinct groups of cryptocurrency users, whose motivations may differ substantially. For example, Bohr and Bashir (2014) analyze a survey of 1,193 early Bitcoin users and find that a substantial part of Bitcoin users identify as libertarians, often attracted by the lack of regulation and government oversight and consistent with many anecdotal stories.[10] Bashir, Strickland, and Bohr (2016) analyze a survey of 520 university students and find that positive attitudes toward Bitcoin are associated with individualism, libertarian ideology, technical skills, anonymity, and novelty, as well as with friends owning Bitcoin, among other things. Hackethal, Hanspal, Lammer, and Rink (2022) study a large sample of indirect cryptocurrency investments through structured retail products and find that cryptocurrency investors are active traders, prone to investment biases, and hold risky portfolios. Pursiainen and Toczynski (2022) show similar findings on direct cryptocurrency invesments.

Another often cited use of cryptocurrencies relates to illicit transactions. Foley, Karlsen, and Putninš (2019) estimate that around $76 billion of illegal activity per year involve bitcoin (46% of total bitcoin transactions). There is also a debate on whether Bitcoin and

[10]For anecdotal evidence, see the commentaries at *https://www.ft.com/content/eeeacd7c-2e0e-11e9-ba00-0251022932c8* and *https://www.businessinsider.com/bitcoin-libertarian-paradise-would-be-hell-on-earth-2013-12?r=US&IR=T.*

other cryptocurrencies should be viewed as investments or currencies used for transactions. Biais, Bisiere, Bouvard, Casamatta, and Menkveld (2022) develop an equilibrium model for the fundamental value of Bitcoin based on the stream of net transactional benefits it will provide, which in turn depend on its future prices. Yermack (2015) argues that Bitcoin appears to behave more like a speculative investment than a currency. Yelowitz and Wilson (2015) study Google Trends data to examine determinants of interest in Bitcoin and find evidence that illegal activity and computer programming are both positively associated with Bitcoin use, while no association exists for Libertarian ideology or investment motives in most specifications. Cryptocurrencies and, closely related, utility tokens have also opened new avenues for financing ventures in the form of initial coin offerings (ICOs) (see, e.g., Howell, Niessner, and Yermack, 2020). Consistent with the trust narrative, Weber (2016) attributes the rise of Bitcoin to a legitimacy crisis of the current monetary and payment system in the aftermath of the financial crisis of 2008.

The literature shows that algorithm-based investment advice (often called "roboadvising") can provide significant benefits for investors' risk-adjusted investment performance (Rossi and Utkus, 2018). The existing evidence suggests it is primarily adopted by wealthier and more sophisticated investors (D'Acunto, Prabhala, and Rossi, 2019). It is possible that algorithm aversion plays a part in reducing investors' willingness to adopt automated investment tools (Dietvorst, Simmons, and Cade Massey, 2015; Dietvorst, Simmons, and Massey, 2018). We are not aware of any study focusing on the role of trust in roboadvisory specifically, although there are studies on trust in delegated portfolio management more generally (see, e.g., Gennaioli, Shleifer, and Vishny, 2015).

The fintech product with probably the most research into the role of trust is peer-to-peer lending. Three papers run fixed-effects regressions on P2P lending and various measures of trust in finance: Saiedi et al. (2020) find a negative relationship between state-level trust in banks based on the General Social Survey (GSS) and the participation of lenders in P2P lending markets. Yang (2021) finds that counties where the Wells Fargo fake accounts scandal was more prominent see higher fintech (P2P lending) usage following the scandal.Finally, Bertsch et al. (2020) find that bank misconduct is associated with an increase in online lending demand at the state and county levels. Somewhat related to this, Tang (2019) shows evidence that P2P lending acts as a both substitute and complement to bank loans.

3 Survey-based analysis

3.1 Data and methodology

The first part of our study consists of a survey using the Longitudinal Internet Studies for the Social Sciences panel. This panel covers a representative sample of nearly 5,000 Dutch households and is administered monthly. While the panel contains standardized questions which are repeated yearly (each month has a separate set of questions), researchers are also able to add their own questions into the survey for a fee. The data generated from these customized questions can then be combined with all previous waves of the survey, allowing a rich set of background data of the survey participants. We add the following custom wave of questions to this survey, measuring trust in finance as well as the use of and interest in various fintech products.

- To measure trust in traditional finance:
  - "In general, do you think most banks can be trusted?" (1-10 scale, 1 meaning disagree completely, 10 agree completely)
  - "What do you think about the effect of increasing involvement of technology in financial services on banks' trustworthiness?" (1-5 scale, 1 meaning "It will make banks much less trushworthy", 5 meaning "It will make banks much more trusthworthy")
- To measure use of different fintech products:
  - "Have you used/invested in the following products:"

- “Are you interested in the following products:”
    - These questions are then followed by a list of the products (cryptocurrencies, a roboadvisor, a non-bank payment app, peer-to-peer lending) along with a brief description of each product and examples of the most popular apps in the Netherlands in each category.
- “Do you have any of the following apps on your phone?”
    - Followed by a list of about 12 popular fintech apps in the Netherlands, mostly related to payment systems, but excluding “default” apps such as Apple Pay or Google Pay that are typically not self-installed.

Note that in our questions we only elicit trust in banks as other waves of the survey have elicited trust in people and other institutions.

3.2 Results

Our survey sample consists of 4,897 people. Figure 1 shows the distribution of trust in banks in the sample. Most respondents have a relatively high level of trust toward banks. Figure 2 plots the average use rates of various fintech products by level of trust in banks. The number of fintech products clearly increases with trust in banks. The pattern for use of cryptocurrency, crowdfunding, or alternative payments is less clear, although the charts might suggest a negative trust relationship for cryptocurrencies and a positive one for crowdfunding and alternative payments.

To study the correlation between trust in banks and general trust in people, we plot the joint distribution in Figure 3. While the figure shows a positive correlation between the two trust variables, there is a lot of variation in trust in banks for every level of trust in people, and vice versa. In other words, trust in people does not explain very much of the variation in trust in banks. In the survey, we also asked whether the increasing use of technology would make banks more or less trustworthy. Generally, people with higher level of trust in banks also believe technology will make banks more trustworthy.[11]

Table 1 shows summary statistics for the sample. The average number of fintech apps is 0.8 and the median 1. The most common apps are iDEAL and Tikkie.[12] About 4% of the respondents have owned cryptocurrency while 5% would consider it.Only 0.3% of the sample have used a roboadvisor. Given the very low adoption rate, we do not perform any statistical analysis on roboadvisors based on this survey, as we lack the statistical power to draw any conclusions. Nearly 2% of respondents have used crowdfunding and 9% alternative payment solutions. 47% of respondents are male, while the average age in the sample is 53. The average income is 2,700 Euros per month.

Using data from earlier waves of the LISS panel survey, we construct variables for financial literacy, financial confidence, and risk aversion. Our *Financial literacy index* is based on four questions testing financial literacy and using factor analysis methodology similar to van Rooij, Lusardi, and Alessie (2011). We construct a measure of financial confidence based on a regression analysis of self-reported financial literacy on measured financial literacy index and define the residual from this regression as *Financial confidence*. This variable measures the over- or underestimation of the respondent of their financial literacy relative to other people with similar level of objectively measured financial literacy. Finally, we use *Risk aversion index* from Noussair, Trautmann, and van de Kuilen (2014) to measure the level of risk aversion in a non-parametric fashion.

Table 2 shows the means of variables divided into users and non-users of cryptocurrencies, crowdfunding, and alternative payments. Cryptocurrency users have somewhat lower average trust in banks than non-users, while crowdfunding and alternative payments users have a higher trust in banks, although this difference is statistically significant only for alternative payments. Across all three products, users are more positive on the effect of technology in improving the trustworthiness of banks. Interestingly, crowdfunding users have significantly

[11] Internet appendix Figure **??** plots this variable, *Fintech effect on trust*, against trust in banks.

[12] Both apps are associated with banks. iDEAL is owned by a consortium and operates through a bank account, Tikkie is owned by ABN Amro and also requires a bank account.

higher trust in people, a characterstic not shared by other fintech product users. The users of all three product types also report a significantly larger average number of fintech apps than non-users.

Cryptocurrency users are substantially more likely to be male and also substantially younger than non-users or the users of other fintech product categories. The users of cryptocurrencies and alternative payments solutions have also significantly higher confidence in science and in internet firms than non-users. All fintech users exhibit somewhat higher financial literacy scores than non-users, although the difference is not statistically significant for any group. Cryptocurrency users also exhibit higher financial confidence, although again not statistically significant. Both cryptocurrency and crowdfunding users have somewhat lower average risk aversion index, although the differences are not statistically significant.

We then test whether trust in finance is associated with usage of fintech products in various categories by estimating regressions of the form:

$$Used\ fintechproduct_i = \alpha_0 + \alpha_1 \times Trust\ in\ banks_i + \beta \times X_i + \epsilon_i \tag{1}$$

where the dependent variable is a dummy taking the value one if the respondent reports having used the particular fintech product. We run this same regression for each of the three product categories in our data (*i.e.,* cryptocurrency, crowdfunding, and alternative payments).

The results are shown in Table 3. The use of cryptocurrencies is associated with slightly lower trust in banks, but this result is statistically insignificant. We find no significant relationship between trust in banks and the use of crowdfunding. The use alternative payments is positively associated with trust in banks. The economic magnitude of the results is also relatively small, both in absolute and relative terms: A 2-standard-deviation increase in trust in banks is associated with an 0.8 percentage point decrease in the probability of owning or having owned cryptocurrencies, or roughly 20% of mean cryptocurrency usage. For crowdfunding, a 2 s.d. increase in trust in banks is associated with a roughly 0.2 percentage point increase in the probability of participating in crowdfunding, or about one quarter of the usage rate.

For comparison, we also include an analysis of having risky investments (including investment funds, bonds, debentures, stocks, and options), shown in columns 7 and 8. We find that participation in risky investments is positively associated with trust in banks, a finding consistent with the results of Guiso et al. (2008) on stock market participation. Given that baseline participation in risky assets is 14.3% in our sample, a 2 s.d. (roughly 4 percentage point) increase in trust in finance is associated with a 3.5 percentage point (25%) increase in risky asset participation. This provides comfort that our sample is not substantially different from those used in prior literature in terms of investment behavior.

We also find that cryptocurrency and crowdfunding users tend to be significantly younger than non-users, politically right of the center. Cryptocurrency users also have higher confidence in science, while alternative payments users exhibit lower confidence in the legal system and higher confidence in internet firms. These characteristics differ somewhat from the typical holders of risky investments, who tend to be older and wealthier, although also politically right of the center and predominantly male.

4 Prolific experiment

4.1 Methodology

To attempt to rule out concerns of unobserved variables driving the observed relationship between fintech adoption and trust in finance, we conduct an experiment in which we prime randomly selected participants to make distrust in finance temporarily more salient. Priming is a frequently used method not only in psychology but also in finance and economics. For example, Cohn et al. (2015) prime financial professionals with either a boom or a bust scenario and show it affects their risk aversion. Other recent priming experiments in economics include Gilad and Kliger (2008), Cohn et al. (2014), and Callen et al. (2014). D'Acunto

(2019a,b) has conducted several experiments similar to our proposed experiment in finance where people are primed with their gender identity or rhetoric from the Occupy Wall Street movement.

Our experiment was pre-registered on the Open Science Framework (OSF)[13] and run on Prolific[14]. Prolific is a platform which allows users to pay participants to complete small tasks and which has been widely used to recruit participants for research in the social sciences. The waves took place between March and May 2022 and we recruited about 5000 participants, all based in the UK or US.

We ran the experiment in 7 different waves (we split up the waves to reach a wider audience). Due to an administrative error, we ended up with slightly more than 5000 participants. All participants in previous experiments and pilots were excluded from subsequent waves meaning that, as far as Prolific's policy on duplicate accounts is enforced, no participant took our surveys multiple times.

4.2 Experiment details

The experiment starts with a consent form explaining the experiment (with as little detail as possible) to participants – we refer to it as a survey on experiences. We then ask all participants to the following questions.

- "Please describe a time you felt mistreated by your friends or family (max. 50 words)."
- "Please describe a time you felt mistreated at work (max. 50 words)."

Both questions featured a prompt asking participants to imagine how they would feel if they were mistreated (with an example) that participants were told to react to in case they could not think of a time they were mistreated.

Next, subjects received one of the following questions.

[13] It is available at https://osf.io/pbtza

[14] We initially ran the experiment on MTurk, but opted to move to Prolific. See our pre-registration statement for more details.

- “Please describe a time you felt mistreated by a financial institution (for example a bank, max. 50 words).”
- “Please describe a time you felt mistreated by a company (for example an airline, max. 50 words).”

Both questions featured a prompt asking participants to imagine how they would feel if they were mistreated (with an example for a bank and an airline) that participants were told to react to in case they could not think of a time they were mistreated.

Randomly chosen half of the subjects (treatment group) received the first question while the other half (control group) received the second question.

In our pre-registration, we mentioned attempting to screen out bots by reading the answers to these questions. After the pilot and several waves, we realized that these were not a big problem on Prolific (as they had been on MTurk), and we subsequently accepted all answers.

As per our pre-registration plan, we also present results excluding those users who provided the shortest answers to our ”priming” questions, i.e. those for whom the priming was likely to have been the least effective. For these analyses, we exclude all participants in the bottom 25% of respondents by the length of their answer (in characters). This screened out participants whose answers were shorter than 143 characters, *i.e.,* shorter than this sentence. Many of these answers simply said that the respondent had not had a bad experience with a company or financial institution.[15]

We, then, elicited participants’ trust in other people and finance by asking them “In general, do you think the following groups/institutions can be trusted? (0-100 point scale)” with the first option (trust in people) being included to get a baseline measure of trust and the middle two institutions being included so as to mask the intention of our experiment (as stated in our pre-registration document).

[15]Screening for inattention via time spent on the survey was another option we considered, but anecdotal evidence and our descriptive statistics suggest that online survey participants are aware that this is commonly used and therefore stretch their survey completion times by working on alternative tasks in a different browser for example.

- People in general
- The government
- Large companies
- Banks

Finally, we ask participants whether they are interested in various fintech and financial products., i.e. our categories of fintech products, stocks and mutual funds. We provide an example for each of the 4 categories of fintech products (*i.e.,* cryptocurrency, peer-to-peer lending,, roboadvisor, and alternative payments) and 2 categories of traditional financial products (stocks, mutual funds), and ask participants about their level of interest (on a scale of 1-7) with an option to tick a box if they use the product or if they do not know what it is. We are mainly interested in people whose decision was affected by our priming, so we exclude people who used these products before and those who did not understand what they were in our analyses. The survey is presented in Appendix IA.1.

4.3 Results

First, we present summary statistics (Table 4) and a t-test of differences in means from the experiments in Table 5. The restricted sample refers to the sample after dropping the bottom 25% of respondents by the length of their answer to the "Treatment" question (please describe a time you were mistreated by a financial institution / company). The summary statistics show that the priming appears to be effective with treated individuals reporting lower levels of trust in banks but without much difference in trust in people. We do not see any large univariate differences in the level of interest in any of the financial products. Untreated respondents seem to show higher levels of interest in stocks, but this difference is not statistically significant in the univariate analysis. Surprisingly, we see almost no difference in interest in mutual funds.

The aim of the experiment is to prime the treatment group's distrust of banks and test whether that results in different levels of interest in various fintech products. Hence, the first thing we assess is the effectiveness of our priming treatment in reducing trust in banks. Figure 4 shows the reported trust in banks for the treatment group and for the control group. We see that the treatment group exhibits lower levels of trust in banks than the control group, suggesting that the priming treatment is effective. As a sanity check, we also compare the reported trust in people for both groups. We find that the general trust level in people is not significantly affected by our treatment, suggesting that we successfully prime distrust toward banks specifically.

We then investigate the differences in reported interest in different fintech products. Figure 5 shows the average level of interest in each product. Visually, the treated group (*i.e.,* those who were primed to distrust finance) appears less interested in stocks and alternative payment systems than the control group. We do not see big differences in interest across any of the other product categories, including (surprisingly) mutual funds.

To formally test whether the decrease in trust in banks caused by the priming affects interest in various fintech products, we perform run an OLS regression[16] of the following form.

$$Interest_{i,j} = \alpha_0 + \alpha_1 \times Treated_i + \epsilon_i \tag{2}$$

where $Interest_{i,j}$ is a 3-point scale response of participant i's interest in product j (*i.e.,* cryptocurrency, peer-to-peer lending, crowdfunding, roboadvisor, and alternative payments), and $Treated_i$ is a dummy taking the value 1 if the participant belongs to the treatment group. In all analyses, we exclude participants who do not know what a product is (even with our description) or already use it.

The results are shown in Table 6. We find no statistically significant differences in rates of interest across any of the fintech products but do find a significant (at the 10% level) lower level of interest for stocks. Economically speaking, all of the differences are quite small - compared to a mean level of interest of about 2, our coefficient of -0.11 implies that people

[16] The results are very similar in unreported ordered logit regressions.

who were asked to recall a bad experience with a financial institution are about 5% less interested in stocks. This is of course to be expected as our treatment variable only induces a minor decrease in the level of trust in finance.

Finally, we examine the association between unconditional level of trust in finance (i.e. the reported trust in finance, not the difference induced by our experiment) and interest in various fintech products. This is useful for two reasons - first, it provides a replication (albeit an incomplete one) of our survey results in a different population. Second, we can test whether the level of trust in finance predicts use of traditional financial products unconditionally, as we expect it should. As we lack the wide range of background variables available in the LISS panel, we expect that we may see a relationship between trust and interest in some fintech products if a control like income is positively associated with both trust and usage of products. We are only able to control for age and gender of the participants.

We present the results in Table 7. We can see that reported trust in finance is associated with statistically significant higher interest in stocks and mutual funds as well in interest in roboadvising. In economic terms, a 25 unit increase in trust (roughly one standard deviation) is associated with a 0.2 unit decrease in reported interest in stocks, or roughly 10% of the mean level of interest.

Thus our "trust" variable, as elicited as part of the experiment, seems to perform as it we predict - it is, conditional on age and gender, positively associated with interest in stocks and mutual funds and only weakly associated with interest in fintech products (other than roboadvisors). This gives us confidence that our null results are not driven by a poor measure of trust.

We have thus shown in the experiment that the experiment lowers levels of reported trust, that reported trust is associated with interest in financial products (but not fintech) and that people in the "treatment" group of our experiment report lower levels of interest in stocks, but not mutual funds or fintech products. While we concede that the experiment lacks power on its own, we note that they should be interpreted *in conjunction* with our survey results, where the problem is the opposite (potential omitted variables).

We now move to the final experiment in our paper.

5 Website experiment

One concern with the Prolific experiment may be that participants are aware that they are being experimented on which may affect their answers (*i.e.,* experimenter demand effect)[17]. In order to address this, we design an experiment where participants are unaware that they are being experimented on. We partner with one of the largest websites dedicated to news and opinions about investing in Finland, with more than 250,000 monthly unique readers (out of a population of 5.5 million).

5.1 Methodology

We worked with the investment website to create a total of five articles designed to stir distrust in finance.[18] We worked in partnership with the website, paying them to write articles, include links and provide us with clickthrough rates through Google Analytics. The website's regular writers wrote the articles on topics that we proposed. The website retained editorial control but allowed us to preview all articles and recommend changes. All articles were advertised through the investment website's social media channels as well as appearing on the front page of their website for a day. The first articles were published in February 2020 and the last ones in November 2020, with roughly one article every two months.

For the first two articles, we created matched control articles that followed the treatment

[17]In fact, at the end of our pilot experiments on Prolific, we asked subjects to guess the aim of the experiment. A significant number of subjects guessed correctly.

[18]The topics of the articles were:

- An article about how crises have affected trust in banks.
- An article about the ECB cracking down on money laundering.
- An article on banks facilitating CumEx dividend trading and hence tax avoidance.
- An article on a data leak revealing the role of banks in tax evasion by the rich.
- An article on fees paid by UK banks for mis-selling insurance products

articles very closely in terms of topic and format (for example, in one pair, the treatment article discussed compensation paid by banks to customers for mis-selling insurance whereas the control article discussed compensation paid by airlines for delayed flights). This format proved to be very inflexible and even with close matching, we saw vastly different readership numbers between the articles, so we switched to a new format where each treatment article was matched with three randomly selected control articles published the same day.

Within each article, we embedded links to "fintech" and "non-fintech" articles. Readers would see a link in the middle and at the bottom of the article, with the content of the link being randomized. We linked to existing articles on the site on various topics and were able to cover all of the categories of fintech other than alternative payments where we were unable to find a suitable existing article.

The links had the following topics:

- Bitcoin as a part of your investment portfolio (crypto)
- Roboadvising comes to Finland - should you pay for a service based on diversification? (roboadvising)
- Experiences and preconceptions about peer-to-peer lending (p2p)
- Peer-to-peer loans are an increasingly popular investment (p2p)
- Is it time to invest in gold? (traditional finance)
- 2-bedroom apartments as an investment (traditional finance)
- Wealth management - an option for you? (traditional finance)
- Is it time to invest in value stocks? (traditional finance)
- Investment guru Seppo Saario becomes an index investor (traditional finance)

5.2 Results

The clickrates for each article category (as a percentage of total tracked clicks) are presented in Figure 6. We see that there are no major differences between treated and control articles in any category, and when differences arise (such as people in control articles being more likely to click on articles about stocks or real estate and less likely to click on articles about cryptocurrencies), they go against the initial hypothesis of trust in finance being associated with higher interest in traditional financial products.

5.3 Reader survey

One concern may be that the readers of our articles are similar in terms of of trust in finance. In order to test whether this is the case, we commission a reader survey. Participants were recruited by links placed into articles offering participants the chance to win a 200 Euro giftcard. The survey asked participants for basic demographic information (age, sex, occupation), financial status (income), trust in finance and financial advisors as well as whether they had invested in a range of financial products or used fintech services. We present some statistics from this survey, divided by whether the reader clicked into the survey from a Treated or a Control article, in Table 8. We can see that trust in finance is higher among those who clicked into the survey from a Control article than those who did so from a Treated article.

Our aim is not to provide suggestive evidence that readers of the treated and control articles are roughly similar in key demographics (they are not) but rather to show that they have different levels of trust in finance. We do not claim that the treatment articles lowered trust in finance (selection effects may play a role), perfect comparability between groups of readers (there are differences in asset market participation) nor that the readers who filled out our survey are necessarily representative of all readers. Instead, the analysis of these demographics is meant as a weak test of whether readers on our treatment articles does indeed trust traditional finance less than readers on our control articles and to provide an overview of potential alternative explanations for observed differences in click rates to articles about financial products.

6 Conclusion

Our results are difficult to reconcile with the prior research on trust and fintech adoption. One reason could be that participants in our survey and experiments are from countries (Netherlands, Finland, the UK, and the US) where financial services providers have generally performed well in recent years in terms of maintaining trust - there have not been a lot of major incidents where customer funds were lost. Our results may not hold in areas where serious scandals have tainted the reputation of financial services providers and forced customers to seek out genuine alternatives to them. In particular the rise of "neobanks" in Latin America, where new providers provide essentially the same services as legacy banks, may have been driven by a deeper lack of trust. Existing papers using US data (e.g. Yang (2021) or Bertsch et al. (2020)) may be able to look at areas of the US where scandals (*e.g.,* Wells Fargo account fraud in 2016) have dented trust more severely. We are also unable to make much use of any time dimension to our results - our data were collected after 2019.

Despite all of these potential limitations, our results suggest that the typical consumer in Western Europe and the US does not seem to consider fintech to be a substitute to traditional financial products, and that trust in finance does not seem to be an important driver in increased usage of fintech in this setting.

References

Allen, Franklin, Asli Demirguc-Kunt, Leora Klapper, and Maria Soledad Martinez Peria, 2016, The foundations of financial inclusion: Understanding ownership and use of formal accounts, *Journal of Financial Intermediation* 27, 1–30.

Andersen, Steffen, Tobin Hanspal, and Kasper Meisner Nielsen, 2019, Once bitten, twice shy: The power of personal experiences in risk taking, *Journal of Financial Economics* 132, 97–117.

Armantier, Olivier, Sebastian Doerr, Jon Frost, Andreas Fuster, and Kelly Shue, 2021, Whom do consumers trust with their data? US survey evidence, *BIS Bulletin* 42.

Bashir, Masooda, Beth Strickland, and Jeremiah Bohr, 2016, What motivates people to use bitcoin?, in Emma Spiro, and Yong-Yeol Ahn, eds., *Social Informatics*, 347–367 (Springer International Publishing, Cham).

Berg, Tobias, Andreas Fuster, and Manju Puri, 2022, Fintech lending, *Annual Review of Financial Economics* 14, 187–207.

Bertsch, Christoph, Isaiah Hull, Yingjie Qi, and Xin Zhang, 2020, Bank misconduct and online lending, *Journal of Banking and Finance* 116, 1–23.

Biais, Bruno, Christophe Bisiere, Matthieu Bouvard, Catherine Casamatta, and Albert J. Menkveld, 2022, Equilibrium bitcoin pricing, *Journal of Finance* Forthcoming.

Bohr, Jeremiah, and Masooda Bashir, 2014, Who uses bitcoin? an exploration of the bitcoin community, *Twelfth Annual Conference on Privacy, Security and Trust (PST)* .

Callen, Michael, Mohammad Isaqzadeh, James D. Long, and Charles Sprenger, 2014, Violence and risk preference: Experimental evidence from Afghanistan, *American Economic Review* 104, 123–48.

Cohn, Alain, Jan Engelmann, Ernst Fehr, and Michel André Maréchal, 2015, Evidence for countercyclical risk aversion: An experiment with financial professionals, *American Economic Review* 105, 860–85.

Cohn, Alain, Ernst Fehr, and Michel André Maréchal, 2014, Business culture and dishonesty in the banking industry, *Nature* 516, 86–89.

D'Acunto, Francesco, 2019a, Identity and choice under risk, Working paper.

D'Acunto, Francesco, 2019b, Tear down this Wall Street: Anti-finance rhetoric, subjective beliefs, and investment, Working paper.

D'Acunto, Francesco, Nagpurnanand Prabhala, and Alberto G Rossi, 2019, The promises and pitfalls of robo-advising, *Review of Financial Studies* 32, 1983–2020.

Dietvorst, Berkeley J., Joseph P. Simmons, and Cad Cade Massey, 2015, Algorithm aversion: People erroneously avoid algorithms after seeing them err, *Journal of Experimental Psychology: General* 144, 114–126.

Dietvorst, Berkeley J., Joseph P. Simmons, and Cade Massey, 2018, Overcoming algorithm aversion: People will use imperfect algorithms if they can (even slightly) modify them, *Management Science* 64, 1155–1170.

Dupont, Quentin, and Jonathan M. Karpoff, 2020, The trust triangle: Laws, reputation, and culture in empirical finance research, *Journal of Business Ethics* 163, 217–238.

Foley, Sean, Jonathan R Karlsen, and Tālis J Putninš, 2019, Sex, drugs, and bitcoin: How much illegal activity is financed through cryptocurrencies?, *Review of Financial Studies* 32, 1798–1853.

Gennaioli, Nicola, Andrei Shleifer, and Robert Vishny, 2015, Money doctors, *Journal of Finance* 70, 91–114.

Gilad, Dalia, and Doron Kliger, 2008, Priming the risk attitudes of professionals in financial decision making, *Review of Finance* 12, 567–586.

Goldstein, Itay, Wei Jiang, and G Andrew Karolyi, 2019, To fintech and beyond, *Review of Financial Studies* 32, 1647–1661.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales, 2004, The role of social capital in financial development, *American Economic Review* 94, 526–556.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales, 2008, Trusting the stock market, *Journal of Finance* 63, 2557–2600.

Hackethal, Andreas, Tobin Hanspal, Dominique M Lammer, and Kevin Rink, 2022, The characteristics and portfolio behavior of bitcoin investors: Evidence from indirect cryptocurrency investments, *Review of Finance* 26, 855–898.

Howell, Sabrina T, Marina Niessner, and David Yermack, 2020, Initial coin offerings: Financing growth with cryptocurrency token sales, *Review of Financial Studies* 33, 3925–3974.

Noussair, Charles N., Stefan T. Trautmann, and Gijs van de Kuilen, 2014, Higher order risk attitudes, demographics, and financial decisions, *Review of Economic Studies* 81, 325–355.

Pursiainen, Vesa, and Jan Toczynski, 2022, Retail investors' cryptocurrency investments, Working paper.

Rooney, Kate, May 2, 2019, The banking revolution is great for customers, Technical report, The Economist.

Rooney, Kate, September 14, 2018, After the crisis, a new generation puts its trust in tech over traditional banks, Technical report, CNBC.

Rossi, Alberto G, and Stephen Utkus, 2018, Who benefits from robo-advising? evidence from machine learning, *Working paper* .

Saiedi, Ed, Ali Mohammadi, Anders Broström, and Kourosh Shafi, 2020, Distrust in banks and fintech participation: The case of peer-to-peer lending, *Entrepreneurship Theory and Practice* 46, 1170–1197.

Tang, Huan, 2019, Peer-to-peer lenders versus banks: Substitutes or complements?, *Review of Financial Studies* 32, 1900–1938.

Thakor, Richard T., and Robert C. Merton, 2018, Trust in lending, NBER working paper.

van Rooij, Maarten, Annamaria Lusardi, and Rob Alessie, 2011, Financial literacy and stock market participation, *Journal of Financial Economics* 101, 449–472.

Weber, Beat, 2016, Bitcoin and the legitimacy crisis of money, *Cambridge Journal of Economics* 40, 17–41.

Yang, Keer, 2021, Trust as entry barrier: Evidence from fintech adoption, Working paper.

Yelowitz, Aaron, and Matthew Wilson, 2015, Characteristics of bitcoin users: an analysis of google search data, *Applied Economics Letters* 22, 1030–1036.

Yermack, David, 2015, *Handbook of Digital Currency*, chapter Is Bitcoin a Real Currency? An Economic Appraisal, 31–43 (Academic Press).

Appendix A: Definitions of variables

Variable	Definition
Survey variables:	
Trust in banks	Response to “In general, do you think most banks can be trusted? (1-10 scale, 1 meaning disagree completely, 10 agree completely)
Fintech effect on trust	Response to “What do you think about the effect of increasing involvement of technology in financial services on banks’ trustworthiness? (1-5 scale, 1 meaning “It will make banks much less trushworthy”, 5 meaning “It will make banks much more trusthworthy”)”
Trust in people	Response to “Generally speaking, would you say that most people can be trusted, or that you can’t be too careful in dealing with people? Please indicate a score of 0 to 10.”
N fintech products	Number of apps the respondent has from our list of 12 most common FinTech apps in the Netherlands
Political left-right	Political orientation based on the question “In politics, a distinction is often made between ”the left” and ”the right”. Where would you place yourself on the scale below, where 0 means left and 10 means right?”
Financial literacy index	Index based on four questions testing financial literacy and using factor analysis methodology similar to van Rooij et al. (2011)
Financial confidence	A measure of financial confidence calculated as the residual from a regression analysis of self-reported financial literacy on measured financial literacy index. Measures the over- or underestimation of the respondent of their financial literacy relative to other people with a similar level of objectively measured financial literacy
Risk aversion index	A non-parametric measure of risk aversion, calculated as the number of risk-averse choices from Noussair et al. (2014) (0-5)
Experiment variables:	
Treated	Dummy taking the value 1 if the suspect was primed to distrust banks by recalling a time they felt mistreated by a bank. The control group was asked to recall a time they felt mistrated by a company.
Trust in banks	Response to the “Banks” section of the question: “In general, do you think the following groups/institutions can be trusted?” (0-100 point scale).
Trust in people	Response to the “People in general” section of the question: “In general, do you think the following groups/institutions can be trusted?” (0-100 point scale).

Figure 1: Survey: Trust in banks

Distribution of *Trust in banks* in the survey sample. Based on the question "In general, do you think most banks can be trusted?" (1-10 scale, 1 meaning disagree completely, 10 agree completely).

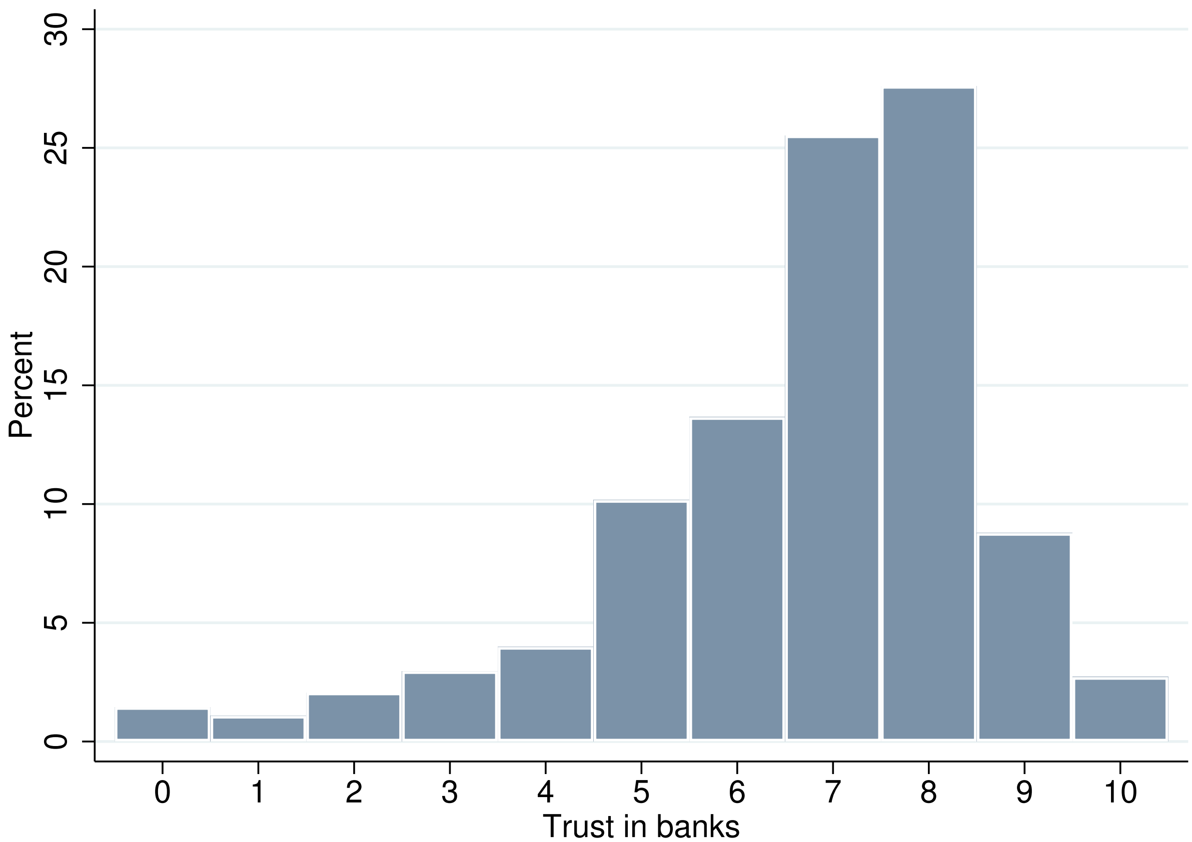


Figure 2: Survey: Reported use fintech products vs. trust in banks

Self-reported use of various fintech products vs. reported trust in banks.

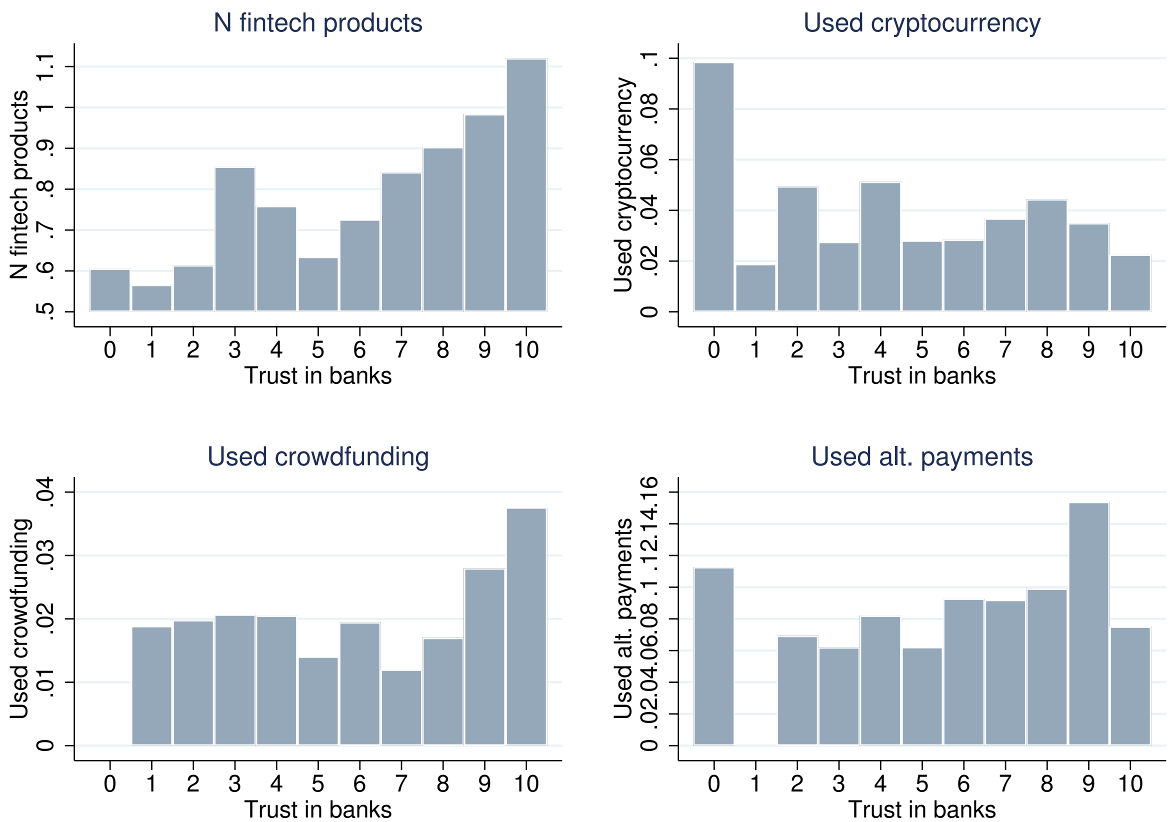


Figure 3: Survey: Trust in banks vs. general trust in people – distribution

The joint distribution of *Trust in banks* vs. *Trust in people.*

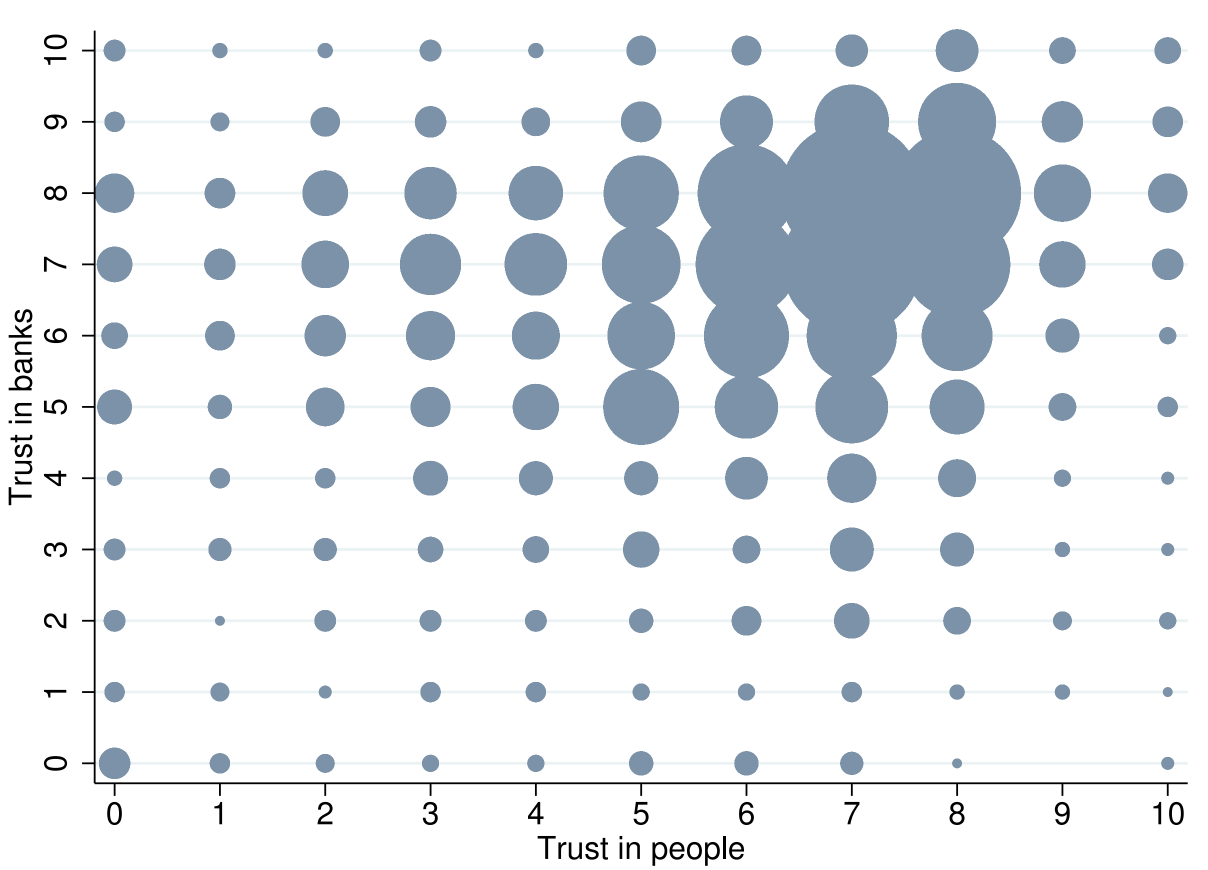


Figure 4: Prolific experiment: Trust in banks vs. trust in people

Average *Trust in banks* and *Trust in people* for the treatment and control groups. 95% confidence intervals are calculated on the basis of heteroskedasticity-robust standard errors.

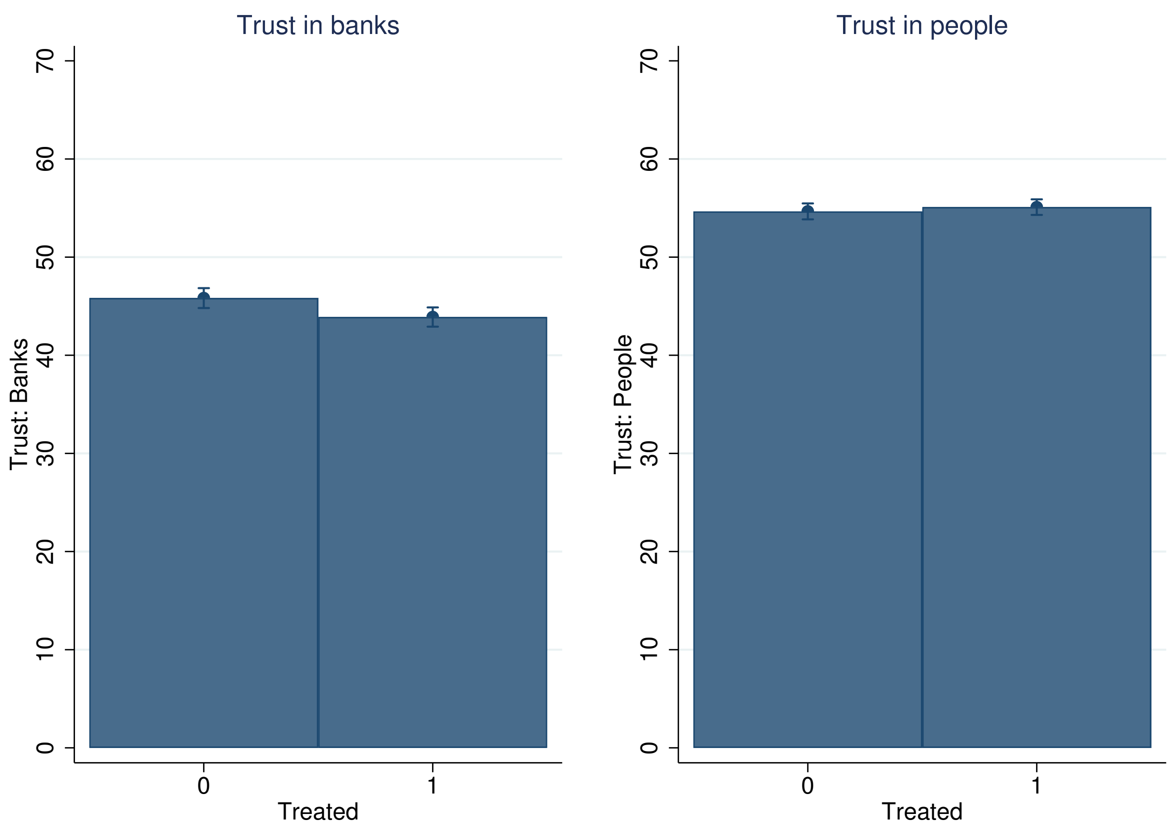


Figure 5: Prolific experiment: Interest in fintech products

The mean level of interest (on a 0-7 scale) by product category in our Prolific experiment. "Treated" respondents were those who were primed to temporarily distrust finance. 95% confidence intervals are calculated on the basis of hetereskedasticity-robust standard errors.

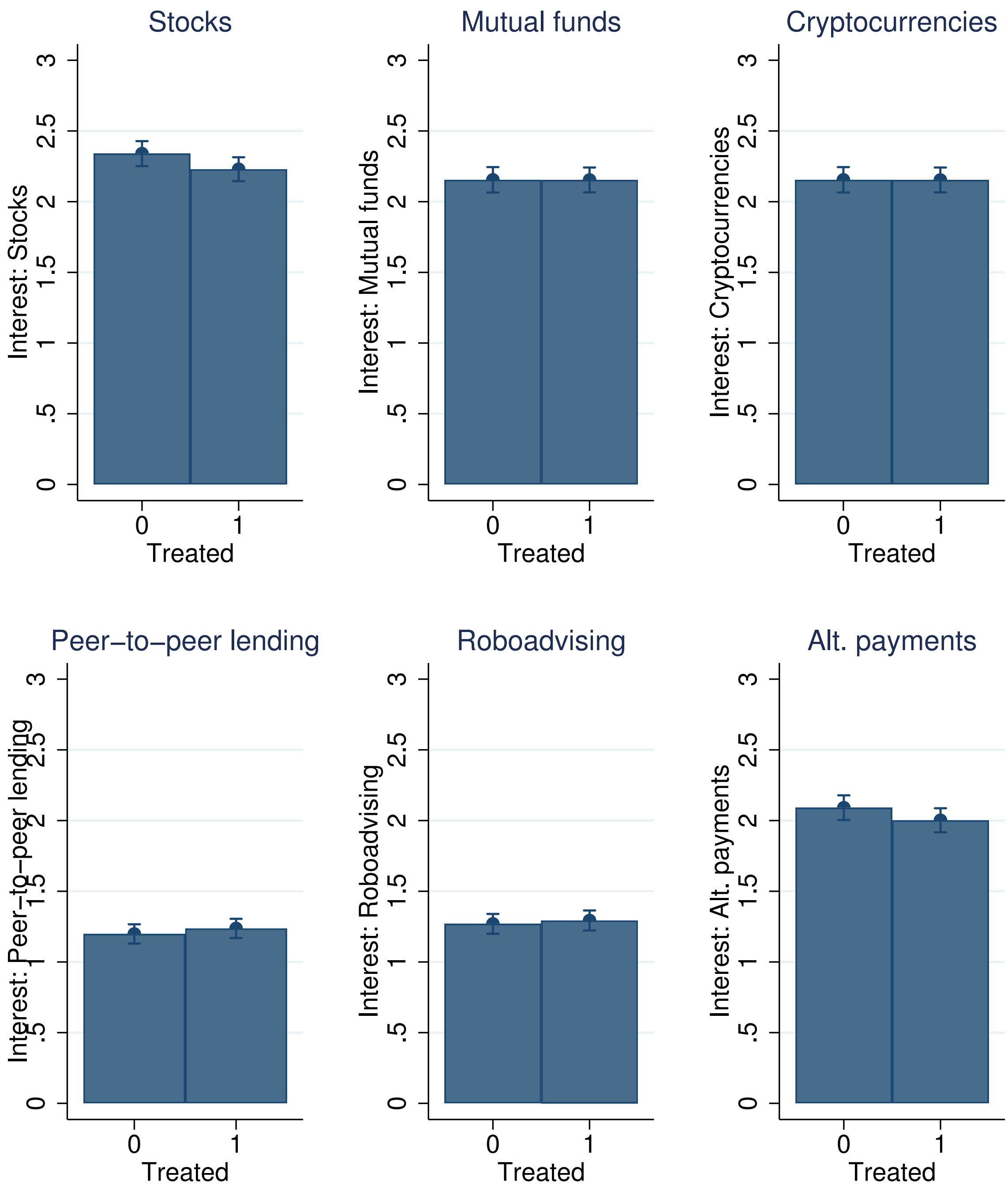


Figure 6: Investment website experiment: Click rates per article

Percentage of tracked clicks to articles in each category in the investment website experiment. Treated articles refer to articles designed to stir distrust in finance. The percentage refers to the number of clicks to articles in each category (e.g. articles related to cryptocurrencies, stocks etc.) divided by the total number of clicks to tracked articles (all our embedded / randomized links).

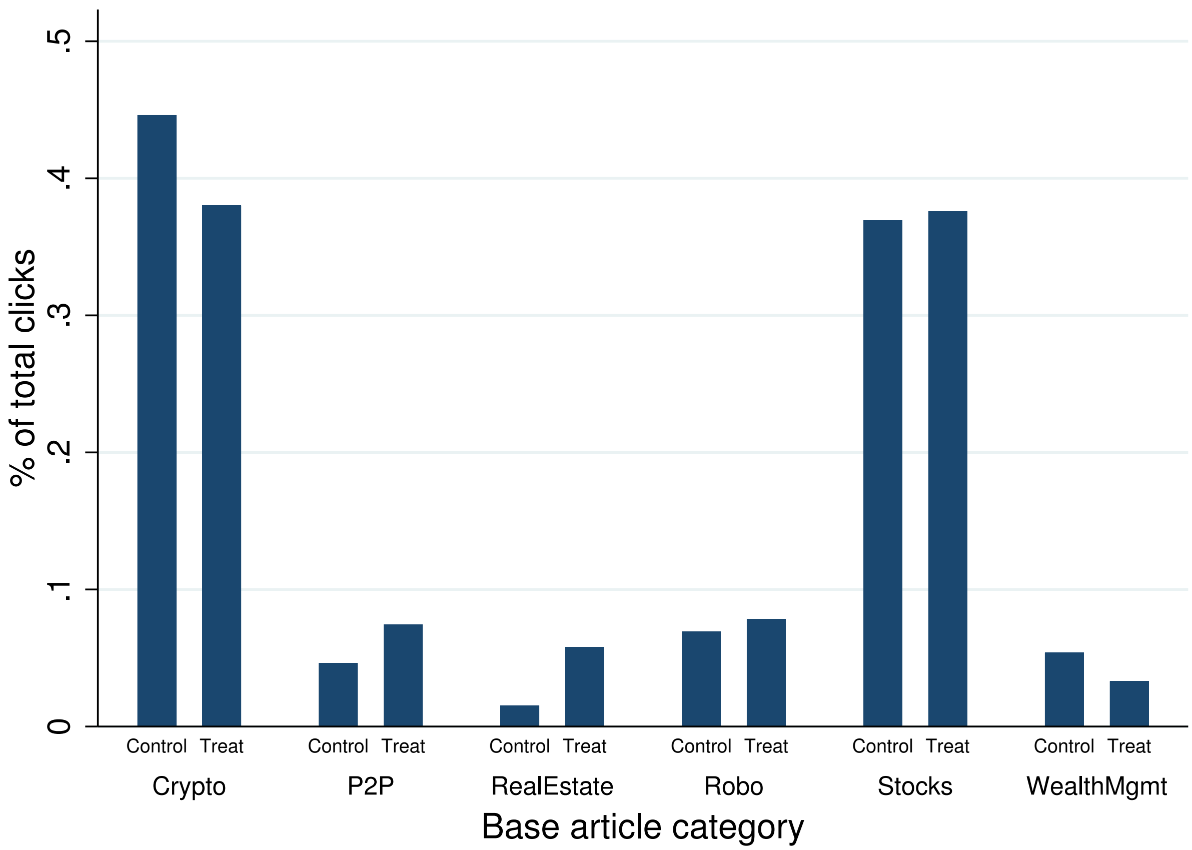


Table 1
Survey: Summary statistics

Summary stats for the survey sample. Variables are defined in Appendix A.

	Mean	Std	p10	p50	p90	N
Trust						
Trust in banks	6.686	1.940	4.000	7.000	9.000	4,897
Fintech effect on trust	2.676	1.054	1.000	3.000	4.000	4,894
Trust in people	6.032	2.177	3.000	7.000	8.000	4,483
Current user						
N fintech products	0.828	1.021	0.000	1.000	2.000	4,895
Tikkie	0.291	0.454	0.000	0.000	1.000	4,895
PayPal	0.114	0.317	0.000	0.000	1.000	4,895
Payconiq	0.004	0.065	0.000	0.000	0.000	4,895
AfterPay	0.042	0.202	0.000	0.000	0.000	4,895
Bunq	0.007	0.083	0.000	0.000	0.000	4,895
Peaks	0.006	0.077	0.000	0.000	0.000	4,895
Knab	0.018	0.132	0.000	0.000	0.000	4,895
N26	0.002	0.047	0.000	0.000	0.000	4,895
iDEAL	0.334	0.472	0.000	0.000	1.000	4,895
Revolut	0.004	0.061	0.000	0.000	0.000	4,895
Twyp	0.001	0.025	0.000	0.000	0.000	4,895
Transferwise	0.005	0.070	0.000	0.000	0.000	4,895
No mobile	0.035	0.184	0.000	0.000	0.000	4,895
Fintech product use						
Used cryptocurrency	0.038	0.190	0.000	0.000	0.000	4,895
Used roboadvisor	0.003	0.053	0.000	0.000	0.000	4,895
Used crowdfunding	0.017	0.131	0.000	0.000	0.000	4,895
Used alt. payments	0.094	0.291	0.000	0.000	0.000	4,895
Interest cryptocurrency	0.053	0.223	0.000	0.000	0.000	4,895
Interest roboadvisor	0.012	0.108	0.000	0.000	0.000	4,895
Interest crowdfunding	0.028	0.166	0.000	0.000	0.000	4,895
Interest alt. payments	0.116	0.320	0.000	0.000	1.000	4,895
Demographics						
Male	0.465	0.499	0.000	0.000	1.000	4,897
Age	52.728	18.340	26.000	55.000	75.000	4,897
Gross income ('000)	2.720	24.508	0.000	2.150	4.500	4,617
Polit. left-right	5.106	2.216	2.000	5.000	8.000	3,910
Conf. - legal system	6.298	2.114	3.000	7.000	9.000	4,525
Conf. - science	7.252	1.594	5.000	8.000	9.000	4,486
Conf. - physical firms	7.000	1.451	5.000	7.000	8.000	4,550
Conf. - internet firms	5.969	1.811	4.000	6.000	8.000	4,434
Fin. literacy index	-0.000	0.722	-0.877	0.312	0.471	2,469
Fin. confidence (index)	0.000	1.246	-2.010	-0.010	1.335	2,469
Risk aversion index	3.386	1.678	1.000	4.000	5.000	1,477
Has risky investments	0.143	0.351	0.000	0.000	1.000	4,553
N	4,897					

Table 2
Survey: Means of variables by product use

Means of variables for the survey sample, divided into users and non-users of different fintech products. Variables are defined in Appendix A. Significance levels: * 0.1, ** 0.05, *** 0.01.

	Cryptocurrency			Crowdfunding			Alt. payments		
	User	Non-user	Diff.	User	Non-user	Diff.	User	Non-user	Diff.
Trust									
Trust in banks	6.598	6.689	-0.091	6.941	6.681	0.260	6.993	6.654	0.340***
Fintech effect on trust	2.989	2.664	0.325***	2.929	2.672	0.258*	2.919	2.651	0.268***
Trust in people	6.000	6.033	-0.033	6.873	6.018	0.855**	6.231	6.013	0.218
Current user									
N fintech products	1.663	0.795	0.868***	1.329	0.819	0.510***	1.841	0.723	1.117***
Fintech product use									
Used cryptocurrency	1.000	0.000	1.000	0.153	0.036	0.117***	0.096	0.032	0.065***
Used roboadvisor	0.005	0.003	0.003	0.012	0.003	0.009	0.009	0.002	0.006*
Used crowdfunding	0.071	0.015	0.055***	1.000	0.000	1.000	0.044	0.015	0.029***
Used alt. payments	0.239	0.088	0.151***	0.235	0.091	0.144***	1.000	0.000	1.000
Interest cryptocurrency	1.000	0.016	0.984***	0.165	0.051	0.114***	0.133	0.044	0.089***
Interest roboadvisor	0.043	0.011	0.033***	0.082	0.011	0.072***	0.031	0.010	0.021***
Interest crowdfunding	0.098	0.025	0.072***	1.000	0.011	0.989***	0.066	0.024	0.041***
Interest alt. payments	0.283	0.109	0.174***	0.294	0.112	0.182***	1.000	0.024	0.976***
Demographics									
Male	0.734	0.454	0.280***	0.518	0.463	0.054	0.498	0.461	0.037
Age	39.054	53.267	-14.212***	47.694	52.822	-5.128*	40.566	53.989	-13.423***
Gross income ('000)	2.960	2.711	0.249	3.331	2.710	0.621	2.726	2.720	0.006
Polit. left-right	5.530	5.090	0.440*	4.685	5.115	-0.430	5.370	5.080	0.290*
Conf. - legal system	6.811	6.279	0.532**	7.154	6.283	0.871***	6.578	6.270	0.307**
Conf. - science	7.885	7.228	0.657***	7.785	7.242	0.542**	7.542	7.223	0.319***
Conf. - physical firms	6.976	7.002	-0.026	7.228	6.997	0.231	7.174	6.984	0.190*
Conf. - internet firms	6.455	5.951	0.504***	6.481	5.960	0.521*	6.547	5.912	0.635***
Fin. literacy index	0.075	-0.002	0.077	0.169	-0.001	0.170	0.055	-0.004	0.059
Fin. confidence (index)	0.120	-0.003	0.123	-0.098	0.001	-0.099	-0.108	0.008	-0.117
Risk aversion index	3.077	3.394	-0.317	2.750	3.391	-0.641	3.455	3.381	0.075
Has risky investments	0.344	0.136	0.208***	0.539	0.137	0.403***	0.162	0.142	0.020
N	184	4,711	4,895	85	4,810	4,895	458	4,437	4,895

Table 3
Survey: Fintech products used vs. trust in banks

The dependent variable, *Used cryptocurrency* (columns 1-2), *Used crowdfunding* (columns 3-4), *Used alternative payments* (columns 5-6), or *Has risky investments* (columns 7-8), takes the value one if the respondent reports having used the product. Variables are defined in Appendix A. Heteroscedasticity-consistent standard errors are shown in parentheses. Significance levels: * 0.1, ** 0.05, *** 0.01.

	Crypto		Crowdfunding		Alt. payments		Risky investments	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Trust in banks	−0.0020	−0.0030*	0.0012	0.0011	0.0064***	0.0049*	0.0088***	0.0061*
	(0.0016)	(0.0018)	(0.0011)	(0.0014)	(0.0021)	(0.0027)	(0.0026)	(0.0032)
ln(Gross income)	0.0068	0.0017	0.0122**	0.0124*	0.0259**	0.0217	0.0759***	0.0890***
	(0.0073)	(0.0092)	(0.0055)	(0.0071)	(0.0114)	(0.0133)	(0.0156)	(0.0185)
ln(Age)	−0.0813***	−0.0857***	−0.0091	−0.0078	−0.1509***	−0.1572***	0.1192***	0.1417***
	(0.0153)	(0.0190)	(0.0084)	(0.0108)	(0.0207)	(0.0260)	(0.0223)	(0.0273)
Male	0.0435***	0.0423***	−0.0020	−0.0043	0.0098	0.0148	0.0545***	0.0486***
	(0.0065)	(0.0073)	(0.0041)	(0.0051)	(0.0096)	(0.0112)	(0.0116)	(0.0136)
Polit. left-right		0.0035**		−0.0012		0.0043*		0.0099***
		(0.0015)		(0.0012)		(0.0023)		(0.0028)
Conf. - legal system		0.0007		0.0014		−0.0064**		0.0042
		(0.0021)		(0.0013)		(0.0030)		(0.0035)
Conf. - science		0.0100***		0.0013		0.0056		0.0018
		(0.0027)		(0.0025)		(0.0040)		(0.0044)
Conf. - physical firms		−0.0035		−0.0021		−0.0031		0.0046
		(0.0030)		(0.0023)		(0.0044)		(0.0052)
Conf. - internet firms		0.0023		0.0015		0.0092***		0.0044
		(0.0018)		(0.0013)		(0.0028)		(0.0040)
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Urbanity FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Education FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4,586	3,500	4,586	3,500	4,586	3,500	4,280	3,371
R^2	0.052	0.058	0.014	0.016	0.066	0.074	0.097	0.102

Table 4
Prolific experiment: Summary statistics

This table presents summary statistics on key variables in our Prolific experiment. The interest variables are coded on a 1-7 scale (from not interested at all to very interested) with those responding that they already use the product or do not know what it is being excluded. The trust variables are coded on a 0-100 scale with 100 meaning "trust completely" and 0 meaning "don't trust at all."

	Mean	Std	p10	p50	p90	N
Trust						
Trust: Banks	44.855	25.973	8.000	48.000	80.000	5.195
Trust: People	54.877	20.897	24.000	59.000	80.000	5.198
Interest						
Interest: Stocks	2.284	2.019	0.000	2.000	5.000	4.185
Interest: Mutual funds	2.154	2.034	0.000	2.000	5.000	4.025
Interest: Cryptocurrency	1.629	1.950	0.000	1.000	5.000	4.353
Interest: Roboadvisors	1.281	1.632	0.000	1.000	4.000	4.123
Interest: Peer-to-peer	1.218	1.579	0.000	1.000	4.000	4.129
Interest: Alt. payments	2.046	1.970	0.000	1.000	5.000	4.013
Demographics						
Age	38.131	12.949	22.000	36.000	57.000	1.390
Male	0.243	0.429	0.000	0.000	1.000	1.390
N	5,201					

Table 5
Prolific experiment: Differences in means

This table presents means and differences of key variables of our Prolific experiment. The sample restriction column only includes observations where the respondent answered the *"Please describe you a time you felt mistreated by a financial institution / company"*-question with more than 143 characters (the 25%-cutoff of the sample). The interest variables are based on a 1-7 scale, with 1 meaning "not interested at all" and 7 meaning "very interested." People who report already using a product or not knowing what it is are excluded from these. Significance levels: * 0.1, ** 0.05, *** 0.01.

	Full Sample			Restricted Sample		
	Treated	Control	Diff.	Treated	Control	Diff.
Response length (priming)	237.990	258.902	20.911***	290.513	307.273	16.760***
Trust: Banks	43.895	45.826	1.931**	44.059	45.719	1.660*
Trust: People	55.093	54.659	−0.434	55.388	54.972	−0.415
Interest: Stocks	2.229	2.340	0.110	2.269	2.367	0.098
Interest: Mutual funds	2.154	2.155	0.001	2.176	2.200	0.024
Interest: Cryptocurrency	1.644	1.614	−0.030	1.598	1.581	−0.017
Interest: Roboadvisors	1.293	1.270	−0.024	1.316	1.241	−0.075
Interest: Peer-to-peer	1.237	1.198	−0.039	1.224	1.187	−0.037
Interest: Alt. payments	2.002	2.091	0.089	2.026	2.086	0.060
N	2,616	2,587	5,203	1,913	2,008	3,921

Table 6
Prolific experiment: Regression results

This table presents results of a regression of the level of interest (0-7) in various financial products on a dummy for whether the participant was "treated "(i.e. received the prompt about a negative experience with a financial institution), from our Prolific study. Panel A presents results from the full sample whereas Panel B from the subsample of users whose answer to the priming question was above the 25th percentile in length ("Attentive sample"). Heteroskedasiticity-robust standard errors are presented in parentheses. Significance levels: * 0.1, ** 0.05, *** 0.01.

Panel A: Full sample

	(1) Stocks	(2) Mutual funds	(3) Crypto	(4) Peer-to-peer	(5) Roboadvising	(6) Alt. payments
Treated	−0.1105*	−0.0010	0.0301	0.0389	0.0236	−0.0888
	(0.0624)	(0.0641)	(0.0591)	(0.0492)	(0.0508)	(0.0622)
Constant	2.3398***	2.1545***	1.6136***	1.1981***	1.2695***	2.0908***
	(0.0450)	(0.0458)	(0.0414)	(0.0348)	(0.0357)	(0.0446)
N	4,185	4,025	4,353	4,129	4,123	4,013
R^2	0.001	0.000	0.000	0.000	0.000	0.001

Panel B: Attentive sample - answer length above 25th percentile

	(1) Stocks	(2) Mutual funds	(3) Crypto	(4) Peer-to-peer	(5) Roboadvising	(6) Alt. payments
Treated	−0.0982	−0.0238	0.0172	0.0370	0.0750	−0.0597
	(0.0723)	(0.0747)	(0.0671)	(0.0562)	(0.0583)	(0.0718)
Constant	2.3671***	2.1996***	1.5809***	1.1872***	1.2411***	2.0861***
	(0.0512)	(0.0522)	(0.0465)	(0.0390)	(0.0398)	(0.0505)
N	3,165	3,028	3,292	3,127	3,124	3,018
R^2	0.001	0.000	0.000	0.000	0.001	0.000

Table 7
Prolific experiment: Unconditional trust and regression results

This table presents results of a regression of interest in various financial products (on a 0-7 scale) on the "trust in banks" variable (as surveyed) from our Prolific study. Panel A presents results from the full sample whereas Panel B from the subsample of users whose answer to the priming question was above the 25th percentile in length ("Attentive sample"). Heteroskedasiticity-robust standard errors are presented in parentheses. Significance levels: * 0.1, ** 0.05, *** 0.01.

Panel A: Full sample

	(1) Stocks	(2) Mutual funds	(3) Crypto	(4) Peer-to-peer	(5) Roboadvising	(6) Alt. payments
Trust: Banks	0.0066***	0.0055***	−0.0007	0.0007	0.0048***	0.0039***
	(0.0012)	(0.0012)	(0.0012)	(0.0010)	(0.0010)	(0.0012)
ln(Age)	−0.8304***	−0.6751***	−0.9554***	0.0600	−0.5375***	−1.4787***
	(0.0881)	(0.0922)	(0.0784)	(0.0717)	(0.0733)	(0.0889)
Male	0.7771***	0.6952***	0.7125***	0.5003***	0.3879***	0.1898***
	(0.0734)	(0.0728)	(0.0726)	(0.0581)	(0.0572)	(0.0671)
Constant	4.7700***	4.1500***	4.9284***	0.8219***	2.8866***	7.1496***
	(0.3228)	(0.3371)	(0.2856)	(0.2572)	(0.2646)	(0.3252)
N	4,164	4,007	4,336	4,105	4,104	3,992
R^2	0.049	0.036	0.050	0.021	0.026	0.065

Panel B: Attentive sample - answer length above 25th percentile

	(1) Stocks	(2) Mutual funds	(3) Crypto	(4) Peer-to-peer	(5) Roboadvising	(6) Alt. payments
Trust: Banks	0.0060***	0.0055***	−0.0009	0.0005	0.0048***	0.0029**
	(0.0014)	(0.0014)	(0.0013)	(0.0011)	(0.0011)	(0.0014)
ln(Age)	−0.8192***	−0.6689***	−0.9130***	0.1243	−0.5295***	−1.5099***
	(0.1019)	(0.1068)	(0.0892)	(0.0816)	(0.0833)	(0.1029)
Male	0.8076***	0.7234***	0.7190***	0.4510***	0.3646***	0.1875**
	(0.0841)	(0.0836)	(0.0820)	(0.0653)	(0.0651)	(0.0765)
Constant	4.7830***	4.1492***	4.7458***	0.5988**	2.8631***	7.3222***
	(0.3723)	(0.3891)	(0.3240)	(0.2925)	(0.3014)	(0.3769)
N	3,150	3,016	3,280	3,110	3,110	3,003
R^2	0.048	0.037	0.050	0.018	0.025	0.067

Table 8
Website experiment: Results of reader survey

This table presents summary statistics from the reader survey of our website experiment. The statistics presented are the mean, divided by whether the participant clicked on the article from a Treatment (inducing distrust) article as well as the difference between Treated and Not Treated. Significance levels: * 0.1, ** 0.05, *** 0.01.

	Treated Article	Control Article	Diff.
Male (0/1)	0.650	0.308	−0.342**
Trust in Banks	51.222	62.957	11.735*
Income below 20k euros	0.050	0.115	0.065
Income 20-30k euros	0.150	0.192	0.042
Income 30-40k euros	0.200	0.192	−0.008
Income 40-50k euros	0.150	0.192	0.042
Income 50-75k euros	0.200	0.154	−0.046
Income 75-100k euros	0.100	0.019	−0.081
Income over 100k euros	0.050	0.096	0.046
N	20	52	72

Internet Appendix

IA.1 Prolific experiment - Qualtrics Files

Screen 1

Survey on your experiences and consumer behaviour

DESCRIPTION: In this survey you will first fill in a form about your past experiences. After this, you will answer questions on your preferences. The survey involves around 5000 subjects, 18 years of age or older who will each participate in a single experimental session. The session that you are participating in today is expected to last around 6-7 minutes.

The survey is conducted by Mikael Paaso (paaso@rsm.nl), Deniz Okat (okat@ust.hk) and Vesa Pursiainen (vesa.pursiainen@gmail.com). The study has been approved by the University of Hong Kong, Hong Kong University of Science and Technology and Erasmus Research Institution for Management Institutional Review Boards.

COST AND PAYMENTS: There are no costs to you from participating in this experimental session other than your time. If you participate and complete the tasks in the experiment, you earn GBP 1 with a potential bonus based on the quality of your answers. Payments will be made through Prolific payment system. Please note that payment is conditional on completing the questions with some minimal level of effort - unrelated answers and bot-generated text will lead to rejection. Assessment of effort is at the researcher's discretion.

CONFIDENTIALITY: In the experiment, we will not ask any question that would help us identify you. We will only obtain your Prolific id and general demographic information of participants from Prolific as well as your IP through Qualtrics. Therefore, your privacy is guaranteed in this study. The survey provider (Qualtrics) and Prolific collect data such as your IP for fraud prevention purposes. Your data, including this consent, will be stored digitally for the duration of the research (up to 10 years). Anonymized data will be made available to other researchers after publication of the study (answers to written questions, IPs, Prolific IDs and any other potentially identifying information will be removed and data such as age will only be published in categorical format). If you wish to have your data removed, please contact Mikael Paaso at paaso@rsm.nl. The data will be held and treated in compliance with the European General Regulation on Data Protection (GDPR) and in accordance with Hong Kong data privacy laws.

RIGHT TO WITHDRAW: During the experiment, you can withdraw at any point of time. In that case, you will not be exposed to any penalty but you will not receive payment for an incomplete survey.

Screen 2

What is your Prolific ID?
Please note that this response should auto-fill with the correct ID

Screen 3

In this section you will be asked about your experiences of unfair treatment. If you have not been treated unfairly, please respond to the prompt below the question.

Please describe a time when you felt unfairly treated by your family or friends (recommended answer length: 50 words)

If you cannot think of a time, please describe how you would feel if your parents constantly favored a sibling over you

Please describe a time when you were unfairly treated at work (recommended answer length: 50 words)

If you cannot think of a time, please describe how you would feel if your boss at work denied you holidays that you had been previously promised

Screen 3 – version 1 (treatment group)

0% 100%

Please describe a time when you were treated unfairly by a financial institution (for example a bank, recommended answer length: 50 words)

If you have NOT been treated unfairly or do not recall an incident, please describe how you would feel if your bank (or another financial institution) charged you a fee that they are entitled to but that you were unaware of without warning.

→

Screen 3 – version 2 (control group)

0% 100%

Please describe a time when you were treated unfairly by a company (for example an airline, recommended answer length: 50 words)

If you have NOT been treated unfairly or do not recall an incident, please describe how you would feel if an airline bumped you off a flight without compensation, causing you to miss an important event.

→

Screen 4

For each of the following institutions, please tell me if you tend to trust it or tend not to trust it (On a scale of 0 being "no trust at all" to 100 "trust completely")

Don't trust at all		A little			A moderate amount			A lot		Trust completely
0	10	20	30	40	50	60	70	80	90	100

People in general

The government

Large companies

Banks

Screen 5

0% 100%

How interested are you in the following products on a scale of 1-7, with 7 being very interested and 1 being not interested at all? (Please answer tick the box at the far right if you already use this product / do not know what it is)

Not at All			Slightly Interested				Very Interested
0	1	2	3	4	5	6	7

Cryptocurrencies (e.g. bitcoin) ☐ I already use this / I do not know what this is

Mutual funds investing in stocks ☐ I already use this / I do not know what this is

Directly investing in stocks ☐ I already use this / I do not know what this is

Peer-to-peer lending (for example: Prosper, Lending Club) ☐ I already use this / I do not know what this is

Alternative payment systems (for example: Venmo, CashApp) ☐ I already use this / I do not know what this is

A roboadvisor for your investments (e.g. Betterment, WealthFront) ☐ I already use this / I do not know what this is

Screen 6

Were you confused/unable to answer any questions in this survey? Please comment freely or leave blank

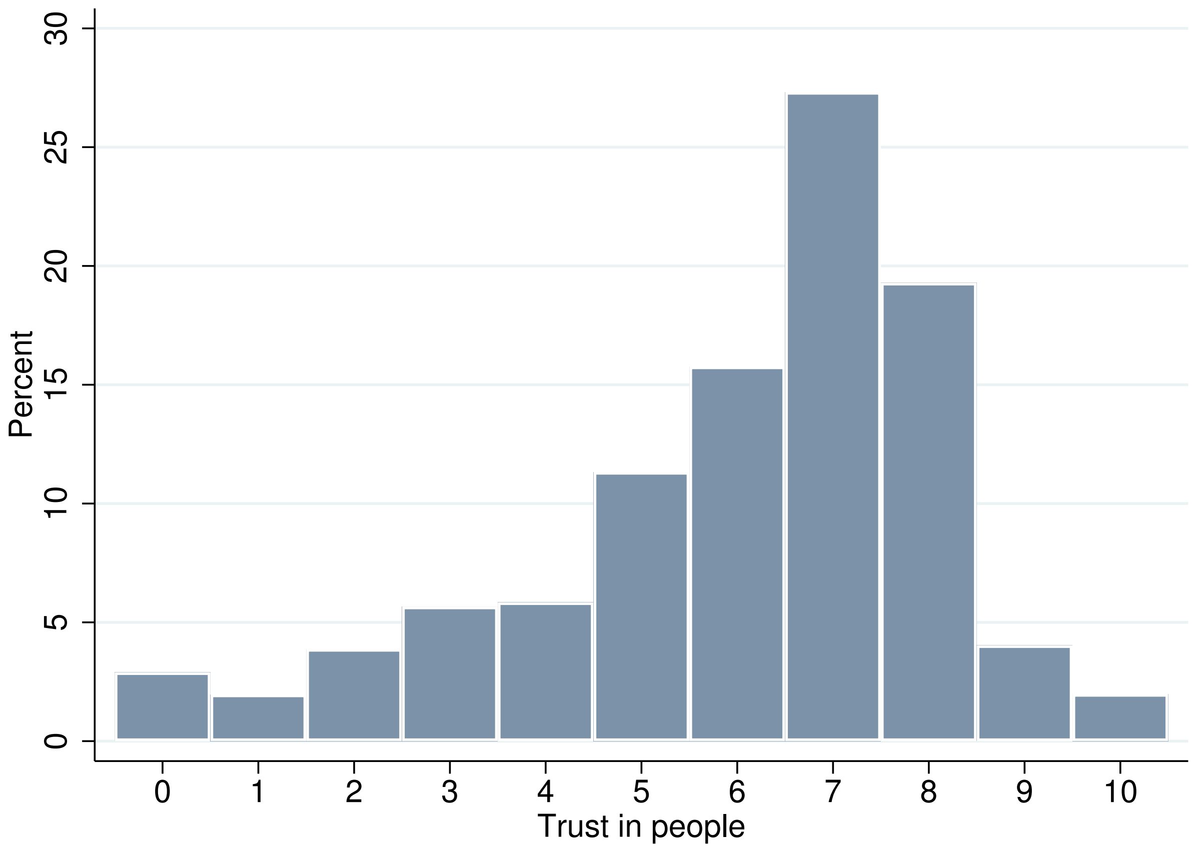
→

IA.2 Additional analysis

IA.2.1 Additional summary statistics

Figure IA.1: General trust in people

Distribution of general trust in people.



IA.2.2 Determinants of trust in banks and people

In this section, we present regression analyses of the determinants of *Trust in banks* (Table IA.1) and *Trust in people* (Table IA.2).

Table IA.1
Survey: Determinants of trust in banks

The dependent variable is *Trust in banks*. Variables are defined in Appendix A. Heteroscedasticity-consistent standard errors are shown in parentheses. Significance levels: * 0.1, ** 0.05, *** 0.01.

	(1)	(2)	(3)	(4)	(5)	(6)
ln(Gross income)	0.3187***	0.4919***	0.3561***	0.2125***	0.4673***	0.3589***
	(0.0552)	(0.0791)	(0.0865)	(0.0558)	(0.0806)	(0.0873)
ln(Age)	−0.3667***	−0.3251***	−0.1629	−0.3925***	−0.4387***	−0.2210
	(0.0676)	(0.1192)	(0.1306)	(0.0690)	(0.1230)	(0.1346)
Male	−0.1452**	−0.1920***	−0.2465***	−0.1139*	−0.1639***	−0.2359***
	(0.0608)	(0.0621)	(0.0669)	(0.0618)	(0.0633)	(0.0686)
Polit. left-right			0.1237***			0.1361***
			(0.0153)			(0.0157)
Conf. - legal system			0.2053***			0.1772***
			(0.0220)			(0.0226)
Conf. - science			0.0243			0.0245
			(0.0303)			(0.0310)
Conf. - physical firms			0.1839***			0.1610***
			(0.0339)			(0.0348)
Conf. - internet firms			0.1066***			0.0892***
			(0.0239)			(0.0246)
Trust in people				0.2009***	0.1986***	0.1204***
				(0.0165)	(0.0169)	(0.0198)
Occupation FE	No	Yes	Yes	No	Yes	Yes
Urbanity FE	No	Yes	Yes	No	Yes	Yes
Education FE	No	Yes	Yes	No	Yes	Yes
N	4,617	4,588	3,501	4,231	4,205	3,309
R^2	0.010	0.028	0.163	0.059	0.076	0.177

Table IA.2
Survey: Determinants of trust in people

The dependent variable is *Trust in people*. Variables are defined in Appendix A. Heteroscedasticity-consistent standard errors are shown in parentheses. Significance levels: * 0.1, ** 0.05, *** 0.01.

	(1)	(2)	(3)
ln(Gross income)	0.5297***	0.2985***	0.2449***
	(0.0653)	(0.0835)	(0.0910)
ln(Age)	0.3127***	0.8739***	0.7986***
	(0.0844)	(0.1430)	(0.1576)
Male	−0.1592**	−0.1462**	−0.1910**
	(0.0704)	(0.0706)	(0.0749)
Polit. left-right			−0.0780***
			(0.0163)
Conf. - legal system			0.2466***
			(0.0239)
Conf. - science			−0.0109
			(0.0347)
Conf. - physical firms			0.1629***
			(0.0391)
Conf. - internet firms			0.0945***
			(0.0286)
Occupation FE	No	Yes	Yes
Urbanity FE	No	Yes	Yes
Education FE	No	Yes	Yes
N	4,231	4,205	3,309
R^2	0.025	0.088	0.191