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Trust in Traditional Finance and Consumer Fintech Adoption

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We study the role of trust in traditional finance in the consumer adoption of various fintech products, including cryptocurrencies, peer-to-peer lending, other crowdfunding, roboadvisors, and alternative payment solutions. Using an online lab experiment, an experiment on an investment website, and a representative survey of Dutch households, we find no consistent evidence that trust in banks affects fintech adoption in any of the product categories, although we find weak evidence suggesting that trust in banks positively affects interest in alternative payment apps. Our results do not support the narrative that trust in traditional finance is a major driver of fintech adoption. (*JEL* D14, G23, G41, G50)

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> An important trigger for the emergence of FinTech has been the loss of trust in central banks and the financial system. It is no coincidence that FinTech came into prominence following the global financial crisis of 2008. – Goldstein, Jiang, and Karolyi (2019)

Academics (e.g., Goldstein, Jiang, and Karolyi 2019; Yermack 2015) and the media commonly explain the substantial increase in fintech usage by pointing to eroding consumer trust in traditional financial systems after the 2008 financial crisis.[1] This narrative argues that a lack of trust in traditional finance has led consumers to seek alternatives in technology-oriented companies and entrepreneurs. The idea goes that technology-oriented companies and entrepreneurs are responding to consumer demands around transparency, trust, and information and filling in gaps left open by traditional financing. Although the narrative of distrust in traditional finance driving fintech adoption is compelling, the popularity of fintech could be related to other reasons, for example, faster processing times, lower operational costs, and improvements in screening provided by recent advances in technology (Berg, Fuster, and Puri 2022).

Fintech is also a very broad term that encompasses many products, meaning that one single narrative does not necessarily fit all cases. Some products, such as many cryptocurrencies, are often 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 and may require an existing bank account. Existing empirical work that provides some evidence of distrust in traditional finance driving fintech adoption is limited to a single class of fintech products, automated loans.[2]

In this paper, we study the role of trust in traditional finance in the adoption of various fintech products, using a combination of experimental and survey-based methods. To motivate our analysis, we set up a simple theoretical model in Internet Appendix Section IA.1, which shows that role of the trust in traditional financial products on adoption to fintech products depends on the degree of substitution between these two products. Our empirical analysis focuses on four specific categories of financial products: cryptocurrencies, roboadvisors, peer-to-peer lending, and nonbank payment systems.

We run two experiments to try to cleanly establish a relationship between trust and interest in these fintech products. The first is an online lab experiment using Prolific, a tool for online experiments, to make distrust in banks

[1] See, for example, The Economist (2019) and Rooney (2018). In Internet Appendix Section IA.2, we offer several examples of media articles, industry reports, industry blogs, and academic blogs that reference this narrative both within and beyond the U.S. context. Fungáčová, Hasan, and Weill (2019) also show that the issue of low trust in banks is not specific to the United States.

[2] See, for example, Saiedi et al. (2020), Yang (2021), and Bertsch et al. (2020).

more salient for randomly selected participants.[3] In the second experiment, we commission articles on a popular Finnish investment website on topics that may stir distrust in banks. Within these articles and a set of "control" articles, we embed randomized links to articles on the selected fintech products and traditional finance topics and measure clickthrough rates to these articles. In addition, we conduct a large-scale representative survey of households in the Netherlands which allows us to study the cross-sectional association between trust in banks and consumer adoption of the selected fintech products while controlling for a wide range of covariates.

Contrary to the common narrative, we find no consistent relationship between the adoption of any of the fintech products and trust in banks. In experiments, individuals who are primed to distrust traditional finance show similar levels of interest towards these fintech products as an unprimed control group, other than perhaps alternative payment apps. In the survey, there is no significant positive association between trust and any of the studied fintech products except payment apps, though even this is generally statistically insignificant. It is important to emphasize that our results do not imply that trust in banks could never matter for fintech adoption but rather that cross-sectional differences in trust or small shocks to trust do not seem to be associated with changes in the adoption of the fintech products we study. It is conceivable that a large shock to trust, for instance repeated fraud by banks, could compel people to seek alternatives and increasingly perceive fintech products as substitutes to traditional finance. It is also worth noting that our measures of trust in banks, described later, might not perfectly capture distrust in the broader financial system that might be important to, for example, early adopters of cryptocurrencies. Nevertheless, we believe our measures capture relatively well general attitudes towards both traditional finance and fintech in wealthy countries.

We begin by conducting an online lab experiment on Prolific in which we aim to temporarily prime randomly selected participants to distrust financial institutions. The idea is to prime distrust in traditional finance in participants.[4] We do this by asking them questions about negative experiences in life. We first ask two unrelated questions that are the same for everyone and then either a priming or a control question (randomized by participant), related to either bad experiences with financial institutions / banks (treatment group) or other firms (control group). We then ask participants about their level of trust in banks 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

3 We use trust in banks to proxy for trust in traditional finance more broadly, as traditional banks are likely to be the most familiar form of traditional finance for participants.

4 Priming is a frequently used method not only in psychology but also more recently in finance and economics. For recent examples, see Cohn, Fehr, and Maréchal (2014), Cohn et al. (2015), Callen et al. (2014), or D'Acunto (2019a, 2019b).

products. In this experiment, we observe close to no differences in interest between the treated and control groups in almost any product category, despite apparently successfully priming the trust levels.[5] While our experiment does not induce large differences in trust in banks, the results are consistent with our other analyses.

One potential drawback of this experiment is experimenter demand effects (i.e., subjects understand that they are being experimented on and may adjust their behavior). While we do not find these demand effects to be very likely, as in our pilot studies (where we explicitly ask participants to guess the purpose of the experiment and offered significant bonuses for doing so) only about 10% of participants understood that we were attempting to stir distrust in banks. However, we still attempt to address this concern by conducting an experiment on a Finnish investment / personal finance website with over 250,000 monthly readers. We work with the website to write articles on topics designed to stir distrust in banks (such as stories about banks paying compensation to customers for misselling financial products), which we call treatment articles, and pair these with control articles chosen randomly from articles published the same day. In these articles we embed (randomized) links to existing articles on selected fintech products (e.g., "Bitcoin as a part of your investment portfolio") and traditional financial products. We then track clicks to the fintech and nonfintech articles from both classes of articles and observe no major differences between click rates in any of the fintech product categories relative to nonfintech articles.

We also test whether cross-sectional differences in trust in banks are associated with use of fintech products in the general population. 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. To elicit trust in traditional 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 banks and in fintech adoption, and we repeat them across two waves (2019 and 2020). We find very little differences in use or trust between the two waves and focus on a cross-sectional analysis of the 2019 data. The richness of the

[5] We also validate our trust measures by showing 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.

LISS panel allows us to control for a range of background variables, including demographics, income, political attitudes, and other factors that might otherwise confound our results.

In the survey, we find that higher trust in banks is positively associated with reported use of alternative payment solutions and the number of fintech apps on one's mobile phone (most of these are associated with banks) and weakly negatively associated with the use of cryptocurrencies. We find no significant relationship between trust in banks and the use of P2P lending platforms.[6] Our results are robust to controlling for age, gender, education, occupation, income, political and societal views, financial literacy, financial confidence, and risk aversion, among other things. The positive correlation between trust in banks and interest in alternative payment systems is in contrast to our experimental results, described below. This may be driven by the fact that almost all payment apps in the Netherlands are closely 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).

In sum, we use a range of methods, including multiple experiments and a large-scale survey, to explore the association between trust in traditional finance and consumer adoption of various fintech products. Contrary to the common narrative, we find no consistent relationship between these. Our results suggest that trust in traditional finance is not an important driver of the consumer adoption of the various fintech products we study – possibly implying that prior studies claiming such relationship should be interpreted with some caution.

1. Relevant Literature

Our paper is related to the broader literature on the role of general and interpersonal trust and financial outcomes. Considerable evidence indicates that trust affects stock market participation and use of traditional financial services.[7] Using data from a peer-to-peer lending platform, Duarte, Siegel, and Young (2012) show that borrowers who appear more trustworthy have higher chance of obtaining a loan. Thakor and Merton (2018) develop a theoretical model of the role of trust in the competition between banks and nonbank lenders, focusing on institution-specific trust, arguing that banks have stronger incentives to maintain trust than nonbank lenders. Armantier et al. (2021) document differences in households' trust to safeguard their personal data in

[6] As in the online lab experiment, to validate our measure of trust in banks, we show that trust in banks is significantly positively associated with holdings of risky investments, consistent with the results of Guiso, Sapienza, and Zingales (2008). This suggests that our measure of trust is consistent with prior literature. We also show that attributes predicting trust in banks are similar to prior literature (e.g., Fungáčová, Hasan, and Weill 2019).

[7] Some examples include Guiso, Sapienza, and Zingales (2004, 2008), Allen et al. (2016), Dupont and Karpoff (2020), and Andersen, Hanspal, and Nielsen (2019).

different types of financial intermediaries (e.g., banks and fintech companies). We add to this literature by focusing on the effect of change in trust in traditional finance on fintech products adoption.

More specifically, our paper is related to the literature on the impact of trust in traditional finance on use of fintech products. It has been suggested (e.g., Yermack 2015; Goldstein, Jiang, and Karolyi 2019) that the rise in fintech usage in the 2010s has been at least partly driven by decreasing trust in finance following the financial crisis of 2008-2009. Research on this question has thus far focused on peer-to-peer lending. Saiedi et al. (2020) find a negative relationship between state-level trust in banks based on the General Social Survey 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 mortgage loan volumes following the scandal. Bertsch et al. (2020) find that bank misconduct is associated with an increase in online lending demand at the state and county level.

A somewhat related question is whether traditional financial products and fintech products are substitutes, complements or unrelated to each other. If fintech was a substitute for traditional finance, we would expect a decline in trust in traditional finance to lead to an increase in fintech usage. Tang (2019) shows evidence that P2P lending acts as a both substitute and complement to bank loans. Contrary to these findings, Erel and Liebersohn (2022) study the response of fintech to financial services demand created by the introduction of the Paycheck Protection Program and find the substitution between fintech and banks economically to be small. In line with this result, our results also suggest that the fintech products we study are not close substitutes to bank lending.

We also contribute to the growing literature on the consumer adoption of different categories of fintech products. This literature has mostly focused on the adoption of cryptocurrencies. While the rise of Bitcoin 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 several distinct groups of cryptocurrency users, whose motivations may differ substantially. For example, Bohr and Bashir (2014) analyze a survey of 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.[8] Bashir, Strickland, and Bohr (2016) analyze a survey of 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 et al. (2022) study a large sample of

[8] For anecdotal evidence, see the commentaries at Wolf (2019) and Edwards (2013).

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 with direct cryptocurrency investments.

2. Theoretical Motivation

In Internet Appendix IA.1, we present a simple model that examines how a decline in trust in the traditional banking system affects the demand for specific fintech products. In this section, we provide an overview of the model and its results.

Our model is centered around the decision of a representative individual who is interested in allocating her endowment between two types of financial products/services. The first type is offered by a traditional bank and could be savings accounts, payment systems, or investment advice. The return on this product depends on the bank's type, which can be either honest or dishonest. An honest bank provides a high positive return for each unit invested, while a dishonest bank provides no return. In our model, each financial service can have its own interpretation of dishonesty. For instance, hidden fees could be a form of dishonesty for money transfer services. In Internet Appendix IA.1, we provide examples of dishonesty for each type of financial service.

The bank's type is unobservable to the individual. Instead, we define trust as the individual's belief that the bank is honest. Our focus is on comparative statics related to this trust parameter. For instance, we analyze how a sudden loss of trust across society would affect the individual's equilibrium choice. Specifically, we investigate how changes in trust affect the allocation of the individual's endowment.

The second type of financial product is provided by a fintech company and could be peer-to-peer lending, cryptocurrency investing, payment apps, or robo-advising. These services are potential competitors to traditional bank products. For example, instead of seeking financial advice from a human at a bank, an individual may choose robo-advising services. The fintech products have a strictly positive probability of generating a positive return, which varies across different services. For peer-to-peer lending, payment apps, and robo-advising, this probability is set to one, indicating full transparency in their fee structures and no uncertainty about their potential returns. However, when investing in cryptocurrency, we assume this probability to be strictly less than one. This assumption captures the idea that mistakes in cryptocurrency investing can have a higher cost.

The individual's preferences exhibit a constant elasticity of substitution, with a parameter α determining the degree of substitution between the bank's and fintech firm's products. For large values of α, the two financial products are perfect substitutes. For smaller values of α, on the other hand, changes in characteristics of one product should have only a little impact on the demand of the other product.

We solve the individual's optimization problem, which involves maximizing her utility by allocating her entire endowment between the two financial products. Using first-order conditions, we perform comparative statics and find that a decrease in trust in the bank's product (weakly) increases the demand for the fintech product. However, we observe that this effect disappears for small values of α. Specifically, a decline in trust for traditional finance only increases the demand for fintech products when these two products are good substitutes (i.e., when α is high). Additionally, since the success probability of cryptocurrency investing is assumed to be strictly less than one, a decline in trust has a relatively smaller impact on cryptocurrency investing compared to other fintech products.

Our experiments aim to test the impact of trust on the adoption of fintech products. Specifically, we will prime subjects to mistrust traditional banking services and observe how this affects their willingness to use fintech products. If mistrust towards banks leads to an increase in fintech adoption, it suggests that fintech products are a viable substitute for traditional banking services (i.e., α is high). Conversely, if there is no relationship between mistrust and fintech adoption, it implies that traditional finance and fintech products are not good substitutes. For empirical tests, the type of traditional banking product or service that is potentially being replaced by fintech is important. For instance, while money transfer through a bank and payment apps may be considered close substitutes, peer-to-peer lending and bank deposits may not be. Furthermore, the ownership of a fintech product is also a significant factor. If a payment app is owned by a bank, then a decline in trust in traditional banking services may also reduce demand for usage of the payment app. Thus, the impact of declining trust in traditional banking on fintech adoption may vary depending on the specific product or service in question.

3. Online Lab Experiment

3.1 Methodology

We begin our analysis by conducting an online lab experiment in which we prime randomly selected participants to make distrust in banks 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, Fehr, and Maréchal (2014), and Callen et al. (2014). D'Acunto (2019a, 2019b) 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 preregistered on the Open Science Framework (OSF) and run on Prolific.[9] Prolific is a platform that allows users to pay participants to complete small tasks and that 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 5,000 participants, all based in the United Kingdom or the United States. We ran the experiment in seven different waves (we split up the waves to try to avoid having our results influenced by any possible time-specific factors, such as surge in some type of respondents on a given day). 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.

3.2 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.

- "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. In the experiment, randomly chosen half of the subjects (treatment group) received the first question while the other half (control group) received the second question.

In our preregistration, 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.

[9] We initially ran the experiment on MTurk, but opted to move to Prolific. Our preregistration statement includes details.

As per our preregistration 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.[10]

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 preregistration document).

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

Finally, we ask participants whether they are interested in various fintech and financial products. In particular, we provide an example for each of the four categories of fintech products (i.e., cryptocurrency, peer-to-peer lending, roboadvisor, and alternative payments) and two categories of traditional financial products (stocks, mutual funds), and ask participants about their level of interest (on a 1- to 7-point scale) 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. Internet Appendix Section IA.4 presents the survey.

3.3 Results

First, we present summary statistics (Table 1) and a t test of differences in means from the experiments in Table 2. 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

[10] 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.

Table 1
Online lab experiment: Summary statistics

	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	38.401	13.367	22.000	36.000	58.000	5.183
Male	0.273	0.446	0.000	0.000	1.000	5.202
N	5,202					

This table presents summary statistics on key variables in our online lab experiment. The interest variables are coded on a 1- to 7-point 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- to 100-point scale with 100 meaning "trust completely" and 0 meaning "don't trust at all."

Table 2
Online lab experiment: Differences in means

	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

This table presents means and differences of key variables of our online lab 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- to 7-point scale, with one meaning "not interested at all" and seven meaning "very interested." People who report already using a product or not knowing what it is are excluded from these. *$p < .1$; **$p < .05$; ***$p < .01$.

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, we first assess the effectiveness of our priming

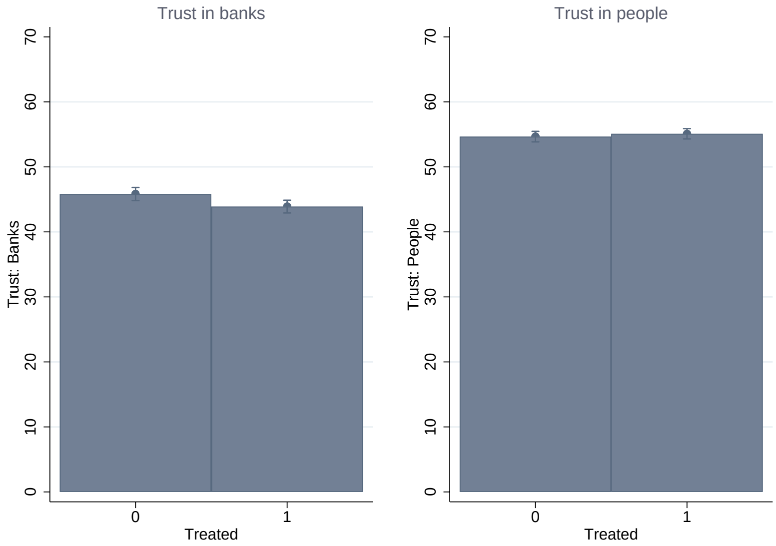

Figure 1
Online lab experiment: Trust in banks versus trust in people
Average *Trust in banks* and *Trust in people* for the treatment and control groups. Ninety-five percent confidence intervals are presented.

treatment in reducing trust in banks. Figure 1 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 2 shows the average level of interest in each product. Visually, the treated group (i.e., those primed to distrust finance) appears less interested in stocks and alternative payment systems than does 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 an ordinary least squares (OLS) regression of the following form:[11]

$$Interest_{i,j} = \alpha_0 + \alpha_1 \times Treated_i + \epsilon_i, \tag{1}$$

where $Interest_{i,j}$ is a seven-point scale response of participant i's interest in product j (i.e., cryptocurrency, peer-to-peer lending, crowdfunding,

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

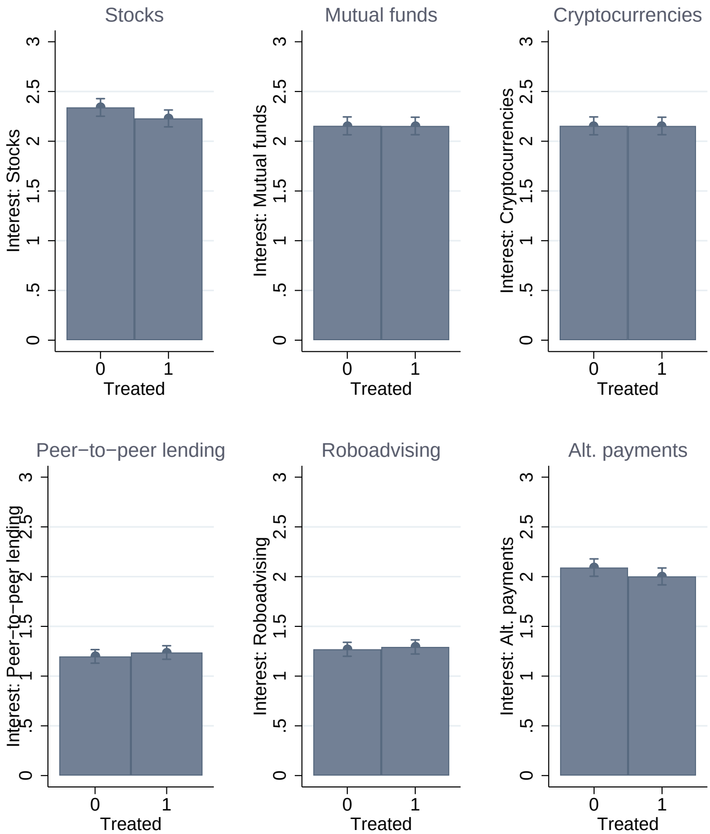

Figure 2
Online lab experiment: Interest in fintech products
The mean level of interest (on a 1- to 7-point scale) by product category in our online lab experiment. "Treated" respondents were those who were primed to temporarily distrust finance. Ninety-five percent confidence intervals are presented.

roboadvisor, and alternative payments), and $Treated_i$ is a dummy taking the value of one 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 3. 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 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 who were asked to recall a bad experience with a financial institution are about 5% less interested in stocks. This is not very surprising, as our treatment variable only induces a minor decrease in the level of trust in banks.

Table 3
Online lab experiment: Regression results

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	.001	.000	.000	.000	.000	.001

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	.001	.000	.000	.000	.001	.000

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 online lab experiment. 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"). Heteroscedasiticity-robust standard errors are presented in parentheses. *$p < .1$; **$p < .05$; ***$p < .01$.

Finally, we examine the association between unconditional level of trust in banks (i.e., the reported trust in banks, not the difference induced by our experiment) and interest in various fintech products. This analysis allows us to test whether the level of trust in banks predicts use of traditional financial products unconditionally, as we expect it should. As we do not have much background information on the participants, we are only able to control for age and gender of the participants (in contrast to the large number of control variables in our LISS survey analysis, which will be described later).

We present the results in Table 4. We can see that reported trust in banks is associated with statistically significant higher interest in stocks and mutual funds as well in interest in roboadvising and alternative payments. In economic terms, a 25-unit increase in trust (roughly one standard deviation) is associated with a 0.2-unit increase 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 – conditional on age and gender, it is positively associated with interest in stocks and mutual funds.

Trust in banks is also positively associated with interest in roboadvisors and alternative payments, but there is no significant relationship between trust

Table 4
Online lab experiment: Unconditional trust and regression results

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	.049	.036	.050	.021	.026	.065

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	.048	.037	.050	.018	.025	.067

This table presents results of a regression of interest in various financial products (on a 1- to 7-point 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"). Heteroscedasiticity-robust standard errors are presented in parentheses. $^*p < .1$; $^{**}p < .05$; $^{***}p < .01$.

in banks and interest in cryptocurrencies or peer-to-peer lending. Given the consistent results on stocks and mutual funds, the null results seem unlikely to be driven by a poor measure of trust.

In conclusion, the experiment lowers levels of reported trust, reported trust is associated with higher interest in traditional financial products (but not two of the main fintech products often invoked in this narrative) and people in the "treatment" group of our experiment report lower levels of interest in stocks, but not mutual funds or the fintech products included. While the experiment likely lacks statistical power on its own, we note that the results should be interpreted in conjunction with our survey results (to be described later), where the problem is the opposite (potential omitted variables).[12]

[12] See Internet Appendix Section IA.8.1 for further discussion on power.

4. Website Experiment

One concern with the online lab experiment may be that participants are aware that they are being experimented on which may affect their answers (i.e., experimenter demand effect). 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 (of a population of 5.5 million).

4.1 Methodology

We worked with the investment website to create a total of five articles designed to stir distrust in banks which were paired with control articles. Internet Appendix Section IA.3 fully lists the treatment articles and control articles. We paid the website to write customized articles for us, including 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 articles very closely in terms of topic and format (e.g., in one pair, the treatment article discussed compensation paid by banks to customers for misselling 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 "nonfintech" 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)

- Two-bedroom apartments as an investment (traditional finance - real estate)
- Wealth management - an option for you? (traditional finance - wealth management)
- Is it time to invest in value stocks? (traditional finance - stocks)
- Investment guru Seppo Saario becomes an index investor (traditional finance - stocks)

4.2 Results

We present the results in Figure 3. The figure plots the total percentage of tracked clicks originating from either treatment or control articles (separately, as there were more clicks to and from treatment articles) to each category of destination article. For instance, the Crypto-bars imply that about 45% of clicks from Control articles went to crypto-related articles and about 38% of tracked clicks from Treatment articles went to crypto-related outcomes articles. There are no large differences between treated and control articles in any category. The largest difference appears in cryptocurrency, but the direction is the opposite of what one would expect if trust in banks were associated with higher interest in fintech products.

One possible explanation might be that the treatment in this experiment is less directly focused on trust in banks than our online lab experiment and might affect other characteristics as well. For example, the treatment articles also might make risk more salient, thereby increasing risk aversion. This

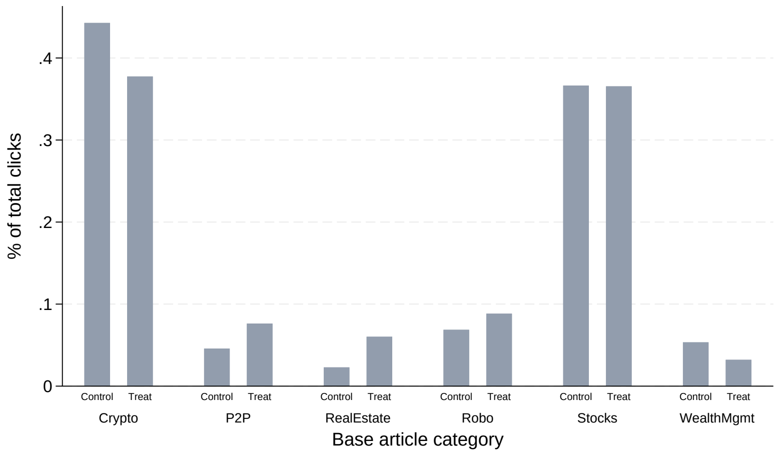

Figure 3
Investment website experiment: Click rates per article
The percentage of clicks to various products as a percentage of total clicks from treatment or control articles in our website experiment. “Treat” articles refer to articles designed to stir distrust in banks and control are the matched and / or randomized control articles.

might at least partly explain why the treatment group exhibits less interest in crypto than the control group, as cryptocurrencies are likely very closely associated with risk. In fact, this is partially captured in our model in Internet Appendix Section IA.1, where we include a (inverse) risk parameter p. The model suggests that a lower value of p indicates a higher likelihood of losing money. In this particular experiment, it is possible that the treatment has lowered both trust in banks and p, generating effects in opposing directions.

4.3 Reader survey

One concern may be that the readers of our articles are similar in terms of trust in banks. 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 banks 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 5. We can see that trust in banks 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 banks. We do not claim that the treatment articles lowered trust in banks (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.

5. Survey-Based Analysis

5.1 Data and methodology

The last 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

Table 5
Website experiment: Results of reader survey

	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

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.
*$p < .1$; **$p < .05$; ***$p < .01$.

customized questions then can be combined with all previous waves of the survey, allowing a rich set of background data of the survey participants.

We add questions to the survey in September 2019 and August 2020, but find little change in people's use of fintech or their trust in banks, making our results essentially cross-sectional. As a result, we present results using only the 2019 data. However, the results for 2020 are very similar.[13]

We add the following custom wave of questions to this survey, measuring trust in banks 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- to 10-point 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- to 5-point 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 nonbank 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?"

[13] The raw data from this wave of the study, as well as other LISS data used, can be accessed via the LISS Data Archive.

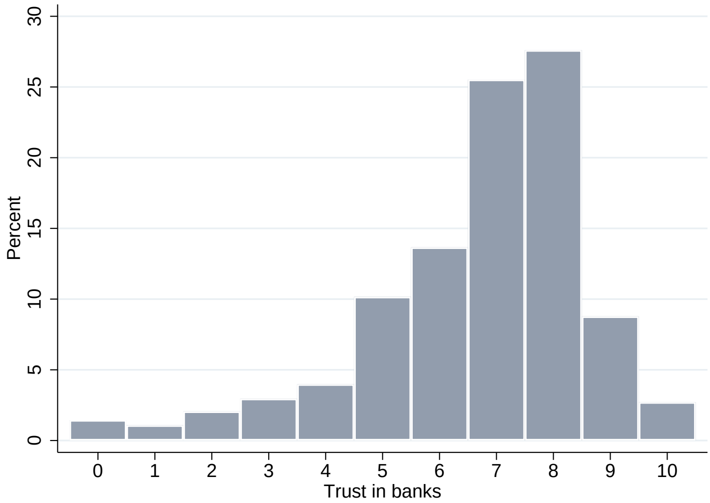

Figure 4
Survey: Trust in banks
Distribution of *Trust in banks* in the survey sample. Based on the question “In general, do you think most banks can be trusted?” (1- to 10-point scale, 1 meaning disagree completely, 10 agree completely).

> * 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.[14]

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.

5.2 Results

Our survey sample consists of 4,897 people. Figure 4 shows the distribution of trust in banks in the sample. Most respondents have a relatively high level of trust toward banks. Figure 5 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, crowd-funding, 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 6. 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

[14] See Internet Appendix Section IA.5 for a description of the apps.

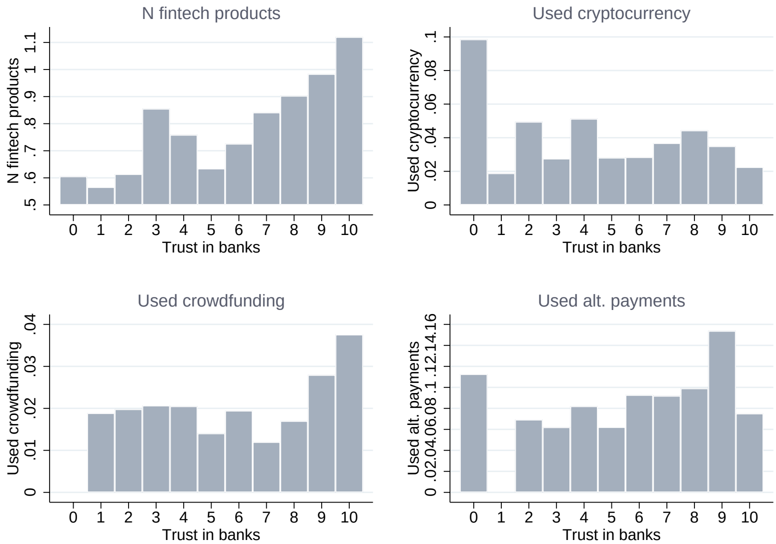

Figure 5
Survey: Reported use fintech products versus trust in banks
Self-reported use of various fintech products versus reported trust in banks.

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.[15]

Table 6 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.[16] 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. Forty-seven percent 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

[15] Internet Appendix Tables IA.4 and IA.5 report determinants of trust in banks and trust in people in our sample. Trust, in general, is associated with income, age, gender, political views, and confidence in legal system and firms.

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

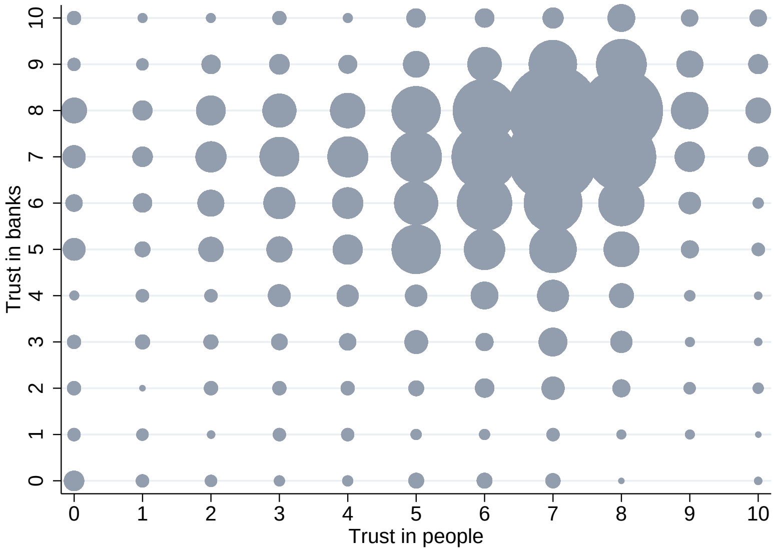

Figure 6
Survey: Trust in banks versus general trust in people, distribution
The joint distribution of *Trust in banks* versus *Trust in people*.

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 nonparametric fashion.

Table 7 shows the means of variables divided into users and nonusers of cryptocurrencies, crowdfunding, and alternative payments. Cryptocurrency users have somewhat lower average trust in banks than nonusers, 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 higher trust in people, a characteristic 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 nonusers.

Cryptocurrency users are substantially more likely to be male and also substantially younger than nonusers 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 nonusers. All fintech users exhibit somewhat higher financial literacy scores than nonusers, although the difference is not statistically significant for any

Table 6
Survey: Summary statistics

	Mean	SD	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					

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

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 banks is associated with usage of fintech products in various categories by estimating regressions of the form:

$$Used\,fintechproduct_i = \alpha_0 + \alpha_1 \times Trust\,in\,banks_i + \beta \times X_i + \epsilon_i, \qquad (2)$$

Table 7
Survey: Means of variables by product use

	Cryptocurrency			Crowdfunding			Alt. payments		
	User	Nonuser	Diff.	User	Nonuser	Diff.	User	Nonuser	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

Means of variables for the survey sample, divided into users and nonusers of different fintech products. Variables are defined in Appendix A.
*$p < .1$; **$p < .05$; ***$p < .01$.

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 8. The use of cryptocurrencies is negatively associated with trust in banks, but the estimated coefficient is only statistically significant at the 10% level when including all control variables. We find no significant relationship between trust in banks and the use of crowdfunding. The economic magnitude of the results is also relatively small, both in absolute and in relative terms: a two-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 the mean cryptocurrency usage. For crowdfunding, a two-standard-deviation increase in trust in banks is associated with a roughly 0.4-percentage-point increase in the probability of participating in crowdfunding, or about one quarter of the usage rate.

The adoption of alternative payment methods is found to be positively associated with trust in banks. In the Netherlands, most payment apps are closely associated with traditional banks, and as such, they are not perceived as separate fintech products. Therefore, changes in trust levels can affect the adoption of payment apps in the same direction as traditional banking products. This can be captured in our model in Internet Appendix Section IA.1 by setting a positive correlation between q (trust in banks) and p (the success probability of a fintech product). Depending on the strength of this correlation, increase in trust may actually increase the demand for payment apps.

For comparison (and to validate our measure of trust), 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, Sapienza, and Zingales (2008) on stock market participation. Given that baseline participation in risky assets is 14.3% in our sample, a 2-SD (roughly 4-percentage-point) increase in trust in banks 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.[17]

We also find that cryptocurrency and crowdfunding users tend to be significantly younger than nonusers, politically right of the center.

[17] Internet Appendix Table IA.6 reports the results of the same analysis by using different control variables, such as financial literacy or risk attitudes. The results are qualitatively the same although around two-thirds of observations drop from the sample.

Table 8
Survey: Fintech products used versus trust in banks

	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	.052	.058	.014	.016	.066	.074	.097	.102

The dependent variable, *Used cryptocurrency* (columns 1 and 2), *Used crowdfunding* (columns 3 and 4), *Used alternative payments* (columns 5 and 6), or *Has risky investments* (columns 7 and 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. $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$.

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.

6. Discussion and Conclusions

None of our methods is perfect. In the online lab experiment, we have perfect randomization, but concerns about a lack of power are legitimate. The experiment on the website may suffer from a selection bias. There is some potential concern for omitted variable bias in our survey approach, as we may not be able to control for all potential variables affecting both trust and the use of fintech products. 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 stock market participation in both the survey and first experiment, among other things.[18] In the first experiment, we additionally show that people's self-reported trust levels (i.e., not variation in trust induced by the experiment) is positively correlated with interest in traditional finance (as well as roboadvisors and payment apps). Despite these concerns, the general consistency of our results across different settings suggests that the common narrative on trust and the rise of fintech should be approached with some caution, as it may not apply to all products and smaller shocks to trust. An alternative explanation to our results would need to explain both why we do not observe any relationship in settings where we are are worried about our results being driven by a lack of power (experiments) and a setting where we are worried about our coefficient estimates being biased due to omitted variables (the survey).

While existing work (e.g., Yang 2021; Saiedi et al. 2020; Bertsch et al. 2020) have documented a relationship between trust and peer-to-peer borrowing, the product category for which we find the most consistent relationship is alternative payment apps. In particular, our survey results indicate a relatively strong association between trust in banks and use of these apps in the Netherlands, while the first experiment implies a weaker, often statistically insignificant, relationship. Part of this may be driven by differences in the setting - alternative payment apps in the Netherlands are typically integrated into the traditional banking system, and some of the most popular apps (Tikkie and iDeal) are owned by banks or consortia of banks. While popular

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

payment apps in the United States, such as Venmo and Zelle, are integrated into the banking system, this may be less salient than in the Netherlands. Interestingly, our results from both experiments suggest that neither our Dutch nor online sample seems to treat cryptocurrencies or peer-to-peer lending as being close substitutes to traditional finance. This might be somewhat expected given the prevalence of alternative (nontraditional) players in both of these fields across richer countries.

Our results are however generally 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 United Kingdom, and the United States) in which financial services providers have generally performed well in recent years in terms of maintaining trust. There have not been a lot of major incidents in which customer funds were lost. Our results may not hold in areas in which 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 U.S. data (e.g., Yang 2021; Bertsch et al. 2020) may be able to look at areas of the United States 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 since our data were collected after 2019.

Despite all of these potential limitations, our results suggest that the typical consumer in Western Europe and the United States may not consider the fintech products (in particular, cryptocurrencies and peer-to-peer lending) we study to be close substitutes to traditional financial products, and that trust in traditional finance does not seem to be an important driver in increased usage of fintech in this setting.

Code Availability

The replication code is available in the Harvard Dataverse at https://doi.org/10.7910/DVN/JA8FFI.

Appendix A

Table A1
Definitions of variables

Variable	Definition
Experiment variables:	
Treated	Dummy taking the value of one 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- to 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- to 100-point scale)
Survey variables:	
Trust in banks	Response to “In general, do you think most banks can be trusted? (1- to 10-point 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- to 5-point 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”
No. fintech products	Number of apps the respondent has from our list of the 12 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 nonparametric measure of risk aversion, calculated as the number of risk-averse choices from Noussair et al. (2014) (0-5)

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