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Blockchain, herding and trust in peer-to-peer lending

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Abstract

Purpose – The gradual implementation of blockchain technology in peer-to-peer (P2P) lending platforms facilitates safer, transparent and quick access to funds without having to deal with the more complex and costly processes of banks. Beyond that, the purpose of this paper is to examine trust-enhancing heuristics that show a need for blockchain to assist in monitoring and bad loan recovery.

Design/methodology/approach – This study examines 909 lending decisions by 303 finance students on a mock P2P site. Each participant was asked to make three lending decisions. The loan applications were identical with the exception of a female or male photo (vs an icon) and reports of having raised half the loan in either 2 or 11 days (vs 7).

Findings – Investors who have experienced financial trauma are more likely to herd and lend higher amounts to loan applicants that are highly trusted by other lenders. This effect is more pronounced for male investors lending to highly trusted female loan applicants.

Practical implications – Blockchain can compensate for behavioral biases and improve monitoring by helping track digital money transactions and assisting in bad loan recovery efforts

Originality/value – This study is the first behavioral experiment to examine herding in P2P lending. The findings complement and corroborate those by Komarova and Gonzalez (2014, 2015) and emphasize the need for blockchain to assist beyond trusted records and safe transfers of funds.

Keywords Financial inclusion, Blockchain, Experimental behavioural finance, Financial trauma, Fintech, Peer-to-peer lending

Paper type Research paper

1. Introduction

Blockchain is an online "trust machine" (*The Economist*, 2015), because it "lets people who have no particular confidence in each other collaborate without having to go through a neutral central authority." It is a decentralized ledger that allows secure, fast and transparent transaction records. It uses cryptography and hashing algorithms, and requires consensus to update records, which make transactions practically tamper-proof and, therefore, more trustworthy. While the full potential of this fast-evolving technology is not yet clear, the applications are numerous and substantial. One of them is online peer-to-peer (P2P) lending, where individuals lend to strangers they meet on the internet. Previous research contends that simple rules, higher IQ and financial literacy lead to acceptable returns in all credit rating (P2P) loan categories with the exception of the high-risk one (Klafft, 2009; Brinblatt *et al.*, 2012; Iyer *et al.*, 2015). However, experimental behavioral studies find evidence of worrisome heuristics that enhance trust and hurt lending decisions even among individuals with higher IQ and literacy than average (Komarova and Gonzalez, 2014, 2015). Overall, lenders favor endorsed loans (Hildebrand *et al.*, 2017) and borrowers deemed trustworthy receive 31 percent more lending bids than average (Duarte *et al.*, 2012). In addition, Komarova and Gonzalez (2014, 2015) find that the gender of borrowers and lenders matters when applications include headshots. In this paper, we dig deeper into the lending decisions of intelligent educated lenders (conservative experimentation) and survey finance students using loan applications with photos from the age group identified by Gonzalez and Komarova (2014, 2015) as most appropriate to study gender. There is no variation in attractiveness, only in gender and

Q1

Q2

JEL Classification — G21, G23, G4

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funding speed. This study hypothesizes that when lenders compare the number of days needed to raise half the funds different applicants seek, there is a tendency to find "popular" loans and applicants "endorsed", more trustworthy, and consequently, indulge in suboptimal herd lending. In addition, we examine herding in relation to gender. Overall, it can be argued that blockchain needs to assist further by helping track the digital transactions of loan funds and helping recover bad loans.

Most P2P online platforms connect potential investors seeking average market returns over 10 percent with individuals seeking average loan amounts of about $10,000[1]. P2P loan services first started in the UK and USA in 2005, and the demand for services increased exponentially during the 2008-2009 liquidity crisis. Within a decade, P2P lending services have expanded as an alternative to banks and credit cards, and by 2020, online P2P lending sites are expected to have provided $290bn worldwide, with over $25bn in small loans to individuals and small businesses (*Financial Times*, 2014). Institutional lenders have taken notice, but although the percentage of P2P lending by institutional lenders has increased, the dollar amounts lent by retail investors continue growing. Some P2P lending platforms, such as SALT, use blockchain and crypto assets as collateral. However, although the World Economic Forum predicts that by 2025, 10 percent of global GDP will be stored on blockchains, governments and regulators around the world fail to recognize cryptocurrencies as legitimate.

P2P services are perceived as convenient, efficient, flexible and empowering. Usual loan application information includes loan purpose, maturity and amount, borrower's credit rating, percentage of the loan application already funded after a certain number of bidding days, interest rate, and on many sites, an image or photograph. Overall, information is limited and lenders do not know the borrowers. Consequently, individual lenders diversify their investments and annual profits vary greatly for investors, as reported in Lendstats.com.

This study is the first to examine how herding in P2P lending relates to borrower characteristics such as financial trauma. The survey sample includes over 909 loan decisions made by 303 undergraduate finance students on a mock site where the only variations are headshot gender (vs an icon) and standard bidding information, reported as the number of days needed to fund half the amount requested by a loan applicant (2 vs 11 days within the 14-day standard bidding period). Since Komarova and Gonzalez (2014, 2015) find similar gender effects in business students and general population, this study surveys finance students, who are arguably best equipped to make lending decisions. It uses attractive male and female headshots within the age range with more clear gender effects (with less age effects).

Overall, the loans that are trusted more by other lenders receive larger bids by survey participants. Interestingly, the effect is stronger when the trusted loan applicant is female and the lender is male, and investors who have experienced financial trauma tend to lend higher amounts to trusted loan applicants.

The remainder of the paper is organized as follows: Section 2 presents the literature review; Section 3 introduces testable hypotheses and describes the sample and variables definition; Section 4 reports the main results of our empirical investigation; and Section 5 concludes and discusses limitations and direction for future research.

2. Literature review

2.1 Online peer-to-peer lending

Person-to-person lending – also known as P2P lending, P2P investing, and social lending, and abbreviated as P2P lending – refers to lending and borrowing between individuals through a for-profit online platform, without the intermediation of a traditional financial institution, although they may participate as lenders. The service started in the UK in 2005, but American platforms quickly took the lead in loan volume. In the direct unsecured P2P lending model, usual loan application information includes loan size, maturity and purpose, percentage of loan funded, bidding days used, some measure of credit rating and interest rate. On some platforms, borrowers can attempt to alleviate information asymmetries by submitting a statement and/or an image. Platform services include calculating interest rates and repayment terms, creating written documents and disbursing funds. Both borrowers and lenders are charged fees, and if the loan defaults, the platform sells it to a debt collection agency[2].

P2P platforms operate similarly all over the world after obtaining clearance from the Securities and Exchange Commission and analogous institutions. As described in Lin *et al.* (2013), users can join US Prosper, for example, by providing an e-mail address that is verified by the website. To engage in a transaction, borrowers must reside in the USA and have a valid social security number, a valid bank account number, a minimum Fair Isaac Credit Organization credit score of 520, and a valid driver's license and address. The details are verified by Prosper.com, which also extracts a credit report from Experian, a major credit reporting agency. Loan proceeds are credited to the bank account and funds are withdrawn automatically for monthly loan repayments. Prosper lenders are also subject to verification of their social security number, driver's license number, and bank account number. To protect privacy, the true identity of borrowers and lenders is not revealed on the website. Communication occurs through usernames that are chosen when signing up.

P2P borrowers get their loan applications listed and active for lender bets until either the loans are either fully funded or the standard two-week listing period ends. Lenders bid the amount they would like to purchase for each loan, and if a listing does not receive enough funding no loan is made, but the borrower can initiate another loan listing.

Once the listing is closed, the platform staff review the closing terms, and sometimes additional documentation is required from borrowers. After the review process is completed, funds are collected from the winning bidders' accounts and transferred to the borrower's account after deducting fees. Loans usually have maturities of up to five years with repayments in equal monthly installments. The monthly repayment is automatically deducted from the borrower's account and distributed to the lenders' accounts. Delinquencies are reported and can affect borrowers' credit scores (Lin *et al.*, 2013).

Lending on P2P sites is risky, because besides limited objective "hard" information about the borrower, lenders face extra adverse selection barriers due to observing credit grade categories rather than actual credit scores (Freedman and Jin, 2017). However, despite the challenges, Iyer *et al.* (2015) find that lenders are, to some extent, capable of estimating the credit worthiness of borrowers. There is a significant heterogeneity in P2P investor returns, but simple rules, higher financial literacy and IQ in lenders appear associated with higher returns (Grinblatt *et al.*, 2012). Similarly, Klafft (2009) finds that following some simple investment rules improves profitability and leads to acceptable returns for all credit rating loan categories with the exception of the highest risk category. However, Gonzalez and Komarova (2014, 2015) find evidence of suboptimal heuristics even among individuals with high IQ and financial literacy, such as business students. More specifically, they use attractive and unattractive variations of borrower headshots within three age groups. They find less age effects and more isolated gender effects in one of the groups, the one used in this paper. Overall, they find that beauty is not always helpful. It can be beastly when male lenders judge attractive male borrowers (as opposed to unattractive male borrowers).

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Most decision makers use heuristics (simple cues) to simplify decisions (Tversky and Kahneman, 1974) to diminish complexity by reducing the number of choices and data points to consider, so less effort and time are needed to arrive at a conclusion. In the context of P2P lending, heuristics are likely to be particularly potent because lenders typically have many alternatives to choose from (Payne *et al.*, 1993) and must evaluate applicants' trustworthiness quickly with limited objective information. While heuristics add great efficiency to any decision-making process, they typically lead to deviations from optimal decisions (Tversky and Kahneman, 1974).

Overall, heuristics are more likely when the loan application includes "soft" information about the borrower. Besides images and messages, many P2P platforms allow borrowers to use their social networks and recommendations to speed up the funding process. Lin *et al.* (2013) find that borrowers with a strong social network receive lower interest rates, and that defaults are less likely for borrowers whose neighbors are also less likely to default. Similarly, Hasan *et al.* (2018) find evidence of stereotyping in debt crowdfunding, with borrowers from high social capital regions enjoying higher funding success, larger loan size and bid size, lower interest rates, and more concentrated loan ownership. In addition, Everett (2015) finds that membership in an online lending community is associated with lower default risk only if membership holds the possibility of real-life personal connections, and Freedman and Jin (2017) find that loans with friends' endorsements and bids have fewer missed payments and yield significantly higher returns. However, Hildebrand *et al.* (2017) find that loans in which lender leaders have "skin in the game" are the only ones more likely to default less.

Typical P2P loan information includes loan percentage already funded in a given number of bidding days. Herzenstein *et al.* (2011) study herding behavior, defined as a greater likelihood of bidding in auctions with more existing bids, i.e. herding. They find that a 1 percent increase in the number of bids increases the likelihood of an additional bid by 15 percent before the loan receives full funding bidding, and conclude that strategic herding behavior in P2P loan auctions benefits bidders. However, the gender effects of Gonzalez and Komarova (2014, 2015) arguably suggest further examination toward more nuanced conclusions.

Overall, despite diversification and other prudent rules of thumb used by most P2P lending investors, information asymmetries lead to substantial subjective lending decisions. This subjective behavior is related to trust-enhancing heuristics (quick information cues) that lead to suboptimal investment portfolios and can limit the financial inclusion of borrowers and lenders. Duarte *et al.* (2012) find that borrowers who are perceived as less trustworthy in P2P lending sites are economically and significantly less likely to have their loan requests filled, even in the presence of adequate contracts and an effective legal system acting as an enforcement mechanism.

2.2 Trust

Investors need to trust to take the risk of departing with their savings hoping that other venues like the stock market and financial institutions will deliver better returns (Guiso *et al.*, 2008). Guiso *et al.* (2008) define trust as the subjective probability individuals attribute to the possibility of being cheated. Recent studies confirm that trust in banks declines significantly during troubled times (Stevenson and Wolfers, 2011; Sapienza and Zingales' Financial Trust Index, Knell and Stix, 2015), especially if there is evidence of conflicts of interest – such as moral hazard – or corruption (Clausen *et al.*, 2011). Stevenson and Wolfers (2011) find that the overall unemployment rate exerts a significant and negative impact on trust measures, which is particularly pronounced for trust in banks. In addition, Jansen *et al.* (2015) find that trust in banks declines sharply following the revelation of large bonuses for bankers, negative media reports and opaque product information. In relation to demographics, Fungacova *et al.* (2018) find that women tend to trust banks more than men[3], and that trust in banks tends to increase with income, access to television and free-market views, but decreases with age, education and internet access[4].

Williamson (1993) argues that, in the presence of adequate contracts and enforcement mechanisms, agents need not consider the trustworthiness of their potential counterparts.

However, as Guiso *et al.* (2004) note, financial contracts are the "ultimate trust intensive contracts," especially when objective information is limited. This is problematic because, despite complexities, trustworthiness assessments are often made rapidly during an initial exchange encounter (Huang and Murnighan, 2010; McKnight *et al.*, 1998).

Chen *et al.* (2014) model and test trust for online P2P lending and show that both trust in borrowers and trust in intermediaries are significant factors influencing lending intention. Furthermore, they find that trust in borrowers nurtures lenders' lending intention and carries the impact of trust in intermediaries. Thus, to develop lenders' trust, borrowers need to provide as much high-quality information as possible and intermediaries need to provide high-quality services and sufficient security protection.

2.3 Blockchain

Blockchain is a distributed ledger protocol or digital database with cryptographic and hashing algorithm safeguards[5]. It is transparent and fast, and cuts out the middlemen, those who usually verify financial transactions, like banks or credit cards. Blockchain requires consensus to add blocks, and enables the decentralized, secure, direct, digital transfer of values and assets across a public or private computing network. Users earn a small fee for validating transactions in a network where all users can read and add transactions, but not edit or erase them. On the down side, it is not yet clear whether it is 100 percent secure, but the network composition makes alterations extremely difficult. In general, the more people who use it the safer it is.

As *The Economist* (2018) points out: "blockchains are best thought of as an idiosyncratic form of database, in which records are copied among all the system's users rather than maintained by a central authority, and where entries cannot be altered once written." Furthermore, the technology is open to low-income countries and economically fragile areas that need more financial inclusion. Overall, a World Economic Forum survey reported that 10 percent of global GDP is expected to be stored on blockchain by 2027.

How does blockchain work? When someone requests a transaction, the requested transaction is broadcast to a P2P network consisting of computers, known as nodes. The network of nodes validates the transaction and the user's status using known algorithms. A verified transaction can involve cryptocurrency, contract, records or other information. Once verified, the transaction is combined with other transactions to create a new block of data for the ledger. The new block is then added to the existing blockchain, in a way that is permanent and unalterable, with a hash that will connect it to the next block. The transaction is then complete.

In blockchain, each computer node in the network holds a copy of the ledger, so there is no single point of failure. Every piece of information is mathematically encrypted and added as a new "block" to the chain of historical records. Various consensus protocols are used to validate a new block with other participants before it can be added to the chain. This allows information to be verified and values to be exchanged without fraud and without having to rely on a third-party central authority. The ledger can also be programmed with "smart contracts," a set of conditions recorded on the blockchain, so that transactions automatically trigger when the conditions are met.

In blockchain, trust is established not by some big institution, but by collaboration, cryptography and clever codes (The Economist, 2015). Unfortunately, blockchain cannot assess whether an external input is accurate or truthful, it can only verify all transactions and data entirely contained on and native to blockchain. Thus, it is not a full truth machine (Carson *et al.*, 2018).

Some P2P platforms use blockchain extensively. For example, SALT allows cryptocurrency traders to use their crypto assets as collateral for loans. Interests range from 10 to 15 percent and loan packages are bigger, up to $1m[6]. Other P2P lending platforms that use blockchain are: Lendoit, 100 percent decentralized and not bound by borders; Kiva for the unbanked and underbanked in developing countries; Bitbond, built over bitcoin; ETHLend and Celsius, built over the Ethereum network; RNC and Jibrel Networks. Interestingly, seven banks including BNP Paribas, HSBC, ING, BNY Mellon and State Street have joined R3 and Finastra to develop a blockchain-powered marketplace for syndicated loans that will cover 10 percent of the syndicated loan market.

By 2024, the global blockchain technology market is expected to be worth \$20bn, and the global P2P lending market is expected to be worth \$1 trillion. Overall, blockchain represents the next chapter of growth for the P2P industry, although national regulations are expected to limit geographical diversification.

3. Methodology

3.1 Hypothesis

The goal of P2P lending is to provide a safe, inclusive, fast and cost-effective alternative to banks and credit cards. Lenders have limited information about the borrowers and perceptions of trustworthiness can lead to suboptimal outcomes for both investors and borrowers (Komarova and Gonzalez 2014, 2015). This is particularly worrisome for lenders who are financially fragile, either because household income is lower or because they have experienced financial trauma. Alesina and La Ferrara (2002) find that interpersonal trust declines with being unsuccessful in terms of income and education or living in an area with high-income disparity. Q4 Overall, individuals who have experienced financial trauma trust banks less (Fungacova *et al.*, 2018; Stevenson and Wolfers, 2011), but do not have lower financial literacy (Gonzalez *et al.*, 2018). In addition, simple investment rules (Klafft, 2009) and higher financial literacy and IQ are associated to higher P2P lender returns (Grinblatt *et al.*, 2012). Thus, investors with high IQ and higher literacy than average, such as a group of finance undergraduate students, would constitute an ideal conservative pool to survey financial trauma and trust-enhancing heuristics in P2P lending. Overall, several hypotheses can be advanced:

H1. Not all individuals place the same amount of trust on the P2P lending model. Lenders more at financial risk may be less aware of risks in P2P lending.

H2. Lenders more at risk may be more susceptible to herding based on the popularity of a loan application.

H3. Lenders who have experienced financial trauma may be more susceptible to images and popularity of loan applications.

H4. Lending decisions may include gender effects in borrowers and lenders.

3.2 Experimental design and procedure

We focus on undergraduate finance students because Komarova and Gonzalez (2014, 2015) find similar gender effects in business students and general population, and finance students have higher financial literacy than average. Like Komarova and Gonzalez (2014, 2015), the experiment uses mixed 2 (between-subjects match between borrower and lender gender: same, opposite)×2 (low and high number of bidding days used with the 50 percent of loan already funded). We also use a control, with a business-related icon in place of headshots and a medium number of bidding days to secure 50 percent funding. The choice of an experimental method is threefold: it allows to control for all irrelevant items to this study information that may otherwise vary on the actual P2P loan applications and impact Q5 the outcome (e.g. loan amount, loan purpose, credit grade, etc.); access to actual P2P lenders, as well as their participation in a research study, is highly unlikely if not impossible, and their real identity is confidential; and importantly, consumer research studies have shown that merely imagining making financial decisions with hypothetical money has the same effect on behavior as actual experiences (Zhu *et al.*, 2012).

In the experimental procedure, participants were first welcomed, thanked for their time and participation, and reminded to read all instructions carefully. All participants were told that they were going to have an opportunity to make lending decisions about three applications and spend funds up to $1,000 on each loan application. Participants were asked to "decide for each loan application whether to fund it or not, as well as how much to allocated to each." As a result, they "may or may not spend the total $1,000 (they) have for each of the three applications" and "any unused funds from the total of $3,000 (they) have been asked to administer would be invested in US Treasury securities." Participants were also reminded that "as any other safe investment vehicle, treasury securities render lower returns than other riskier options." All participants were also told that the goal was to "compete" toward higher return on investment.

Participants were introduced to the mock P2P lending site LENDI, read a basic description of how it functions (please see Appendix 1 for a screenshot), and were told about a variety of purposes for which one may decide to borrow money via LENDI. In addition, they were explained the possible risks involved, the type of information that is typically available on LENDI loan applications, and were given further instructions (see Appendix 2 for a screenshot). This type of information is standard in online social lending sites. Next, participants were randomly assigned three applications: one female, one male and one gender-neutral icon loan application. The loan applications were identical with the exception of a female or male photo (vs an icon), as well as a high difference in trust by other lenders. Other lenders were reported to favor either the male or the female loan application (50 percent funded in 2 days within the 14-day bidding period, vs 11 days needed for the other gender applicant and 7 days for the icon applicant) (see Appendix 3). The headshots are selected among the attractive headshots used in Komarova and Gonzalez (2014, 2015) within the most suitable age range to examine gender effects.

3.3 Sample description

The sample consists of 909 P2P lending responses by 303 undergraduate finance students, of which 187 are males and 116 females. After making three P2P lending decisions each, participants were asked to complete a section in which they reported their age, household income, level of investing experience, trust in banks and P2P lending, and whether or not they had experienced financial trauma, Overall, over 80 percent of the experiment participants are less than 25 years old, gross annual household income varies greatly (from below $25,000 to above $100,000), and more than half survey participants have experienced financial trauma.

4. Empirical evidence

Table I introduces the coding criteria for male and female gender of survey participants, who are the lenders or investors in the behavioral experiment. It also specifies the options given to participants to rank their investing experience, projected financial literacy ("if financial services professionals were to evaluate your investor literacy") as well as trust in banks, bankers, P2P model, debt collection agencies, people and those on P2P sites. It also specifies the coding for whether the more trusted loan application is the one with the male or the female photo. In addition, participant lenders are asked to rank the probability of loan default and their confidence regarding their investment decision.

4.1 Univariate statistics

As shown in Panel A of Table II, the sample size is very diverse in terms of ethnicity. About a quarter of the participants identify themselves as Caucasian, a third as Asian and a third

Variable name	Coding
Lender gender	1 – male; 0 – female
Ethnicity	1 – Caucasian; 2 – African American; 3 – Asian; 4 – Latino; 5 – Other
Household annual income	1 – 20–60 K; 2 – 60–100 K; 3 – over 100 K
Finance work experience	1 – yes; 0 – no
Investing experience	1 – none; 2 – modest; 3 – moderate; 4 - substantial
Projected financial literacy	1 – minimal to 7 – outstanding
Trust banks more than stock market	1 – yes; 0 – no
Trust bankers more than stock market	1 – yes; 0 – no
Finds P2P riskier than stock market	1 – yes; 0 – no
Trust in banks	1 – great deal, 2 – quite; 3 – not much, 4 – none
Trust in people	1 – yes; 0 – no
Trust in P2P people online	1 – yes; 0 – no
Trust debt collection agencies	1: great confidence; 2: quite a lot; 3: not much; 4: none
Popular borrower – 50% raised in 2 bidding days out of 14-day bidding period	1 – male; 0 – female
Loan1	\$ Lent (out of \$1,000) to Loan Application 1 instead of invested in treasury securities
Loan1Default	Loan: 1, Borrower: 0 – unlikely to 10 – very likely to default
Loan1Sure	0 – not much to 10 – very sure about decision

Table I.
Coding criteria

as Latino. They are mostly not religiously active, and more than half are males. Participants have limited work and investing experience, as well as limited projected financial literacy (see Footnote 4). Interestingly, they remember that there was a crisis in 2008, when they were in primary school, but they do not remember clearly the blame on the banks. Overall, they tend to trust banks more than the stock market and do not seem aware of the extra risks when investing in P2P lending, although they claim not to trust to people much, whether in person or on P2P online. About half of survey participants have entrepreneur and loan application experience, and most importantly, more than half have experienced financial trauma.

Q15

Panel B of Table II shows that male participants are slightly older lenders with a slightly higher household income. Female lenders report lower investment experience and lower projected financial literacy than males. Among finance students, females do not report to trust banks more than males, like Fungacova *et al.* (2018) find for the general public, but interestingly, females trust debt collection agencies more than males. Thus, females are arguably at a greater risk when lending in P2P sites. Overall, this heterogeneity in trust and risk perceptions is consistent with *H1*.

Panel C of Table II reports that most survey participants either were born in the USA or have lived in the USA since early childhood. Interestingly, the lenders that have experienced financial trauma have lived longer in the USA and are more likely to have applied for a loan in the past.

Table III presents summary statistics of the 909 P2P lending decisions. As anticipated in *H2*, and explained by investors following their lending decisions, experiment participants were paying close attention to loan popularity (loans trusted by other lenders) and photos, and less attention to the numerical details of the loan applications. In consequence, when the female loan application was reported to be more trusted among lenders, the median lending decision was \$800 for the female application and \$500 for the less-trusted male application. Same when the male application was reported to be more trusted. Interestingly, experiment participants found the trusted female loan application less likely to default than the trusted male loan application, and the less-trusted male loan application more likely to default than the less-trusted female loan application. Thus, it

Panel A: By ethnicity: 1 – Caucasian; 2 – African American; 3 – Asian; 4 – Latino; 5 – other

	Caucasian, $n = 70$		African American $N = 9$		Asian, $n = 95$		Latino, $n = 102$		Others, $n = 27$	
	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.	Mn.	Med.
Age	22.56	21	30.33	22	22.72	21	22.68	22	22.2	22
Years in the USA	19.2	21	26.44	22	16.57	20	20.3	21	19.2	21
Gender	0.7	1	0	0	0.48	0	0.67	1	0.81	1
Religiously active	0.27	0	0.77	1	0.32	0	0.22	0	0.41	0
Household income										
Finance courses taken	2.67	2	6.5	4.5	2.88	2	2.93	3	2.17	2
Finance work experience	0.27	0	0.44	0	0.21	0	0.26	0	0.19	0
Investment experience	1.7	2	2	2	1.54	1	1.75	2	1.93	2
Projected financial literacy	3.06	3	3.33	3	3.08	3	3.36	3	3.52	3
Entrepreneur experience	0.61	1	0.77	1	0.46	0	0.47	0	0.7	1
Ever applied for a loan	0.44	0	1.33	1	0.33	0	0.57	1	0.37	0
Financial trauma	0.5	0.5	0.67	1	0.54	1	0.59	1	0.48	0
Trusts banks over stocks	0.5	0.5	0.66	1	0.55	1	0.56	1	0.59	1
Does not trust banks	0.74	2	2	2	1.77	2	1.82	2	1.74	2
Bankers worse than average	0.26	0	0.33	0	0.36	0	0.31	0	0.19	0
Trusts people	0.43	0	0.78	1	0.44	0	0.38	0	0.41	0
P2P riskier than stocks	0.47	0	0.44	0	0.47	0	0.42	0	0.52	1
Trust P2P people online	0.4	0	0.67	1	0.37	0	0.3	0	0.48	0
Trust debt col agencies	2.32	2	3	3	2.26	2	2.55	2	2.19	2

Panel B: By gender: 1 – male lender; 0 – female lender

	Male, $n = 187$		Female, $n = 116$	
	Mean	Median	Mean	Median
Age	22.81	22**	22.92	21
Born in the USA	0.78	1	0.74	1
Years in the USA	19.21	21	18.43	21
Religiously active	0.26*	0	0.35	0
Household Income	1.92**	2**	1.72	1.5
Finance courses taken	2.7	2	3.09	2
Finance work experience	0.26	0	0.23	0
Investment experience	1.83**	2**	1.49	1
Projected financial literacy	3.38**	3	3	3
Entrepreneur experience	0.53	1	0.52	0
Ever applied for a loan	0.48	0	0.45	0
Safe neighborhood	0.88*	1	0.81	1
Financial trauma	0.56	1	0.52	1
Trusts banks over stocks	0.59	1	0.5	0.5
Does not trust banks	1.75	2	1.85	2
Bankers worse people than average	0.28	0	0.35	0
Trusts people	0.41	0	0.44	0
P2P riskier than stocks	0.49	0	0.41	0
Trust P2P people online	0.41	0	0.44	0
Trust debt collection agencies	2.33*	2	2.49	2

Panel C: by financial trauma

	Has experienced it, $n = 166$		Has not experienced, $n = 137$	
	Mean	Median	Mean	Median
Age	23.21	22	22.4	22
Born in the USA	0.81**	1	0.7	1

Table II.
Lender summary statistics

(*continued*)

Years in the USA	20.05**	21	17.53	21
Gender	0.63	1	0.59	1
Religiously active	0.27	0	0.32	0
Household income	1.78	2	1.91	2
Safe neighborhood	0.84	1	0.86	1
Finance courses taken	2.97	2	2.74	2
Finance work experience	0.25	0	0.26	0
Investment experience	1.67	2	1.76	2
Projected financial literacy	3.28	3	3.2	3
Entrepreneur experience	0.57	1	0.49	0
Ever applied for a loan	0.55**	0	0.36	0
Trusts banks over stocks	0.53	1	0.58	1
Does not trust banks	1.79	2	1.79	2
Bankers worse people than average	0.34	0	0.27	0
Trusts people	0.42	0	0.42	0
P2P riskier than stocks	0.53	1	0.58	1
Trust P2P people online	0.36	0	0.39	0
Trust debt collection agencies	2.45	2	2.34	2

Notes: The behavioral experiment is based on 909 P2P lending decisions made by 303 undergraduate finance students between May 2017 and August 2018. For Panels B and C: *,**Significantly different at 0.05 and 0.1 levels, respectively

Table II.

seems that there is higher trust placed on female applications trusted by other lenders. This is consistent with experimental findings by Komarova and Gonzalez (2014, 2015) regarding attractive male and female borrowers.

Panels B and C of Table III further detail the summary statistics of the lending decisions. Again, the strongest differences are in the subsample of loan decisions in which the female loan applicant was reported to be more trusted and able to raise 50 percent of the requested loan amount in 2 days out of a bidding period of 14 days (as opposed to 11 days in the case of the male applicant). When the female applicant is reported to be more trusted, male lenders that have experienced financial trauma tend to lend more (as opposed to investing in low-risk low-return treasury securities), and also report higher confidence in their decision than the female lenders. Thus, males appear to be also at risk when lending in P2P sites, for different reasons than female investors. This is consistent with *H1–H4*.

4.2 Analyses and empirical results

Table IV examines the effect a number of factors could have in the perceptions of risk. As expected, higher financial literacy is related to the higher perceptions of risk when investing in P2P lending sites, as compared to investing in the stock market. However, given the high amounts lent to all P2P loan applications, the risk of P2P lending vs investing in Treasury securities is arguably underestimated regardless of differences in financial literacy. In addition, like Fungacova *et al.* (2018), lower income is associated with lower trust in banks.

Table V examines which factors could be driving the different lending decisions. Consistent with summary statistics, those experiment participants that have experienced financial trauma are significantly more likely to lend a higher amount to a female loan application that is reported to be trusted among other investors. This is consistent with *H1–H3*.

Arguably, as more P2P lending platforms adopt blockchain, the loan contracts should allow only digital money transactions of borrowed funds. Cryptocurrencies are valued collateral, mitigate risks and improve loan funding at competitive rates, but there are other options. Once P2P platforms adopt blockchain, borrowing contracts could require the digital use of borrowed funds, like PayPal or Paytm. Paytm is used in India, for example, to ensure that a loan to purchase cattle, for example, is used for that purpose.

Table III. Lending decisions summary statistics

Panel A

	Female borrower more popular		Male borrower more popular	
	Mean	Median	Mean	Median
Loan1 – female borrower	706.33**	800**	570.44	500
Loan2 – male borrower	468.67**	500**	685.22	800
Loan3 – icon borrower	536.6	500	560.8	500
Loan12	237.65**	275**	−114.78	0
Loan13	169.73**	175**	9.65	0
Loan23	−67.93**	0**	124.43	131
Loan1Default	3.52**	3**	4.17	4
Loan1Sure	6.63	7	6.43	7
Loan2Default	5.04**	5**	3.92	3
Loan2Sure	6.06	7	6.5	7
Loan3Default	4.57	5	4.31	5
Loan3Sure	6.11	7	6.12	7

Panel B: female applicant (Loan1) more popular

	Female lender		Male lender		No financial trauma		Financial trauma	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Loan1	649	700*	732.52	800	634**	600**	763.92	800
Loan2	439	400	480.58	500	467.33	400	460.76	500
Loan3	501	500	548.86	500	572.33*	500	489.34	500
Loan12	210	150	251.94	300	166.67*	200*	303.16	300
Loan13	148	100	183.66	200	61.67**	50**	274.58	200
Loan23	−62	0	−68.28	−100	−105	−100	−28.58	0
Loan1Default	3.29	3	3.57	3	3.81	3	3.24	3
Loan1Sure	5.68**	5**	7	8	6.43	7	6.73	8
Loan2Default	5.39	5	4.84	5	5	5	5.09	5
Loan2Sure	5.2**	5.5**	6.43	7	6.04	7	6.06	6
Loan3Default	4.63	5	4.51	4	4.65	5	4.52	5
Loan3Sure	5.16**	5**	6.53	7	5.98	7	6.22	7

Panel C: male applicant (Loan2) more popular

	Female lender		Male lender		No financial trauma		Financial trauma	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Loan1	597.4	500	555.29	500	625.68	500	533.52	500
Loan2	700.72	800	680.71	800	695.38	800	688.18	800
Loan3	570.72	550	559.34	500	645.46	500	505.33	500
Loan12	−103.3	0	−125.4		−69.71	−100	−154.66	0
Loan13	26.65	0	−4.05	0	−19.78	0	28.19	0
Loan23	130	100	121.37	200	49.92	100	182.85	200
Loan1Default	3.86	4	4.39	5	3.97	4	4.26	4
Loan1Sure	626	6	6.53	7	6.65	7	6.28	7
Loan2Default	4.14	4	3.69	3	4.25	4	3.59	3
Loan2Sure	6.32	7	6.61	7	6.63	7	6.43	7
Loan3Default	4.55	5	4.07	5	4.17	5	4.36	5
Loan3Sure	5.81	6	6.34	7	6.14	6	6.13	7

Notes: The behavioral experiment is based on 909 P2P lending decisions made by 303 undergraduate finance students between May 2017 and August 2018. Some loan applications are popular among lenders and half funded within 2 days since the loan was posted (14-day listing period), while others are reported to be less popular among lenders and are half funded within 11 days of bidding. Loan1, 2 and 3 shows bids out of $1,000 toward each loan application. Loan12 shows the difference in bids by the same lender toward Loan 1 (female borrower) over Loan 2 (male borrower). Loan 3 application has a generic icon instead of a photo. Popular loans are those that have secured 50 percent funding in 2 days (vs 11 for less popular loans and 7 for icon application) with the standard bidding period of 14 days. For Panels A and B: *,**Significantly different at 0.05 and 0.1 levels, respectively

	P2P riskier than stock market	Banks less risky than stock market
Lender gender	0.080 (1.3)	0.09 (1.52)
Age	0.007 (1.79)	0.03 (0.75)
Projected financial literacy	0.05 (2.64)	−0.01 (−0.55)
Financial trauma	−0.01 (−0.21)	−0.08 (−1.34)
Household Income	0.004 (0.11)	−0.07 (−1.95)
Religiously active	0.05 (0.72)	−0.06 (−0.91)
Constant	0.06 (0.5)	0.64 (4.12)
R^2 (%)	10.4	5.9
n	300	300

Notes: The sample consists of over 909 P2P lending decisions made by 303 undergraduate finance students. Male lender is coded as 1, female lender is coded as 0. The Female Loan 1 is popular equals 1 when lenders commit to fund half the loan in a 2 bidding days, as opposed to the male loan applicant that takes 11 bidding days to fund half the loan (in a 14-day bidding period). *T*-statistics are reported in parenthesis

Table IV. Determinants of risk perception with respect to stock market

	Loan 1: female popular	Loan 2: male popular	Loan 3: when female loan 1 popular
Lender gender	72.35 (1.34)	−33.73 (−0.57)	33.93 (0.69)
Age	−7.9 (−1.01)	−10.48 (−1.54)	−1.48 (−0.2)
Investment experience	23.35 (0.74)		27.55 (0.94)
Projected financial literacy		42.43 (1.94)	
Financial trauma	81.19 (2.06)	21.72 (0.4)	−84.19 (−2.23)
P2P riskier than stock market	−57.87 (−1.18)	−41.62 (−0.74)	−31.71 (−0.68)
Household income	−26.77 (−0.88)	2.79 (0.08)	−8.73 (−0.29)
Religiously active	39.94 (0.78)	−18.83 (−0.29)	−17.13 (−0.31)
Constant	81.59 (4.13)	82.4 (4.75)	91.12 (3.04)
R^2 (%)	10.9	9.6	6.6
n	150	150	150

Notes: The sample consists of over 909 P2P lending decisions made by 303 undergraduate finance students. Male lender is 1, female lender 0. The female loan 1 is popular equals 1 when lenders commit to fund half the loan in a 2 bidding days, as opposed to the male loan applicant that takes 11 bidding days to fund half the loan (in a 14-day bidding period). *T*-statistics are reported in parenthesis

Table V. Determinants of lending decisions

In addition, similar to mortgage contracts with banks, contracts that use blockchain could easily include recourse clauses regarding asset sales. This is essential in countries where debt collection agencies have lower reputation and P2P lending platforms do not offer any kind of lender insurance.

5. Conclusions

Blockchain is an online "trust machine" (The Economist, 2015) and P2P lending an alternative to banks in online platforms where lenders have limited information about borrowers. The gradual implementation of blockchain technology in P2P lending platforms facilitates transparent safe access to funds without having to deal with the complex settlements and processes of banks. However, other uses of blockchain may be in need.

This study is the first behavioral experiment to examine P2P lending decisions subject to herding when investors compare basic bidding information. The findings complement and corroborate those by Komarova and Gonzalez (2014, 2015) on a mock P2P site, and emphasize the need for blockchain to assist beyond the trusted records and safe transfers of funds. Trust-enhancing heuristics and biases are common among intelligent finance educated lenders. This leads to suboptimal lending decisions. The good news is that the use of blockchain technology can arguably compensate for heuristics and biases. Specifically, blockchain technology can improve loan monitoring by tracking the digital use of loan funds toward the stated loan purpose. Furthermore, if a borrower defaults, blockchain can assist in bad loan recovery efforts.

Specifically, this study examines 909 lending decisions by 303 finance students on a mock P2P site. Each experiment participant was asked to make three P2P lending decisions. The loan applications were identical with the exception of a female or male photo (vs an icon), as well as a high difference in trust by other lenders. Other lenders were reported to favor either the male or the female loan application (50 percent funded in 2 days within the 14-day bidding period, vs 11 days needed for the other gender and 7 days for the icon applicant). Overall, the investors who have experienced financial trauma are more likely to herd and lend higher amounts to loan applications that are highly trusted by other lenders. This effect appears more pronounced for male investors lending to trusted female applications.

Arguably, when P2P lending platforms adopt blockchain, the contracts should allow only digital money transactions of borrowed funds. Some P2P lending platforms allow the use of collateral, in the form of cryptocurrencies. This mitigates risks and can improve loan funding and repayment, but there are other options. Once P2P platforms adopt blockchain, borrowing contracts could require the electronic use of funds to enforce the stated loan purpose. In addition, contracts that use blockchain can easily include recourse clauses on asset sales. This is key to financial inclusion in countries where debt collection agencies have a poor reputation.

Notes

1. Borrowers with excellent credit are usually charged 10.4 percent interest on credit cards and 6.7 percent on P2P sites. Borrowers with good credit are charged an average 14.91 percent interest rate on credit cards and about 7.16 percent on P2P sites. Borrowers with fair credit are charged an averaged 23.3 percent on credit cards and 17.3 percent on P2P sites.
2. Some sites arrange lender insurance agreements.
3. Sapienza *et al.* (2013) argue that World Values Survey trust questions capture mostly the belief-based component of trust. Guiso *et al.* (2006) define culture as those customary beliefs and values that ethnic, religious and social groups transmit fairly unchanged from generation to generation.
4. In a related study, Gonzalez *et al.* (2018) show that students who have experienced financial trauma do not have lower financial literacy. Gonzalez and Komarova (2014, 2015) explain that P2P lending settings are likely to induce stress.
5. Blocks are chained using hash technology, immutable digital keys that further protect the integrity and immutability of the coded information by linking blocks with electronic fingerprints.
6. Usually, P2P loans are smaller than in SALT, where in order to borrow \$100,000, up to \$200,000 in bitcoin would be expected as collateral, for 12–20 percent interest a year. Usually, in over 40 sites around the world, average loan sizes vary greatly and do not surpass \$50,000 in the USA (Gonzalez, 2017), and interest rates can be as low as 6–9 percent. In the USA, historical loss rates are below 15 percent in the riskiest loan category of returns circa 15 percent.

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Appendix 1

Appendix 2

Instructions

For the purpose of this study, you will have an opportunity to make ***three lending decisions about three loan applications****, assuming you can spend* ***up to $1,000 in each of them. Each loan application you will evaluate will be randomly selected from a pool of actual loan applications****. We are interested in better understanding how potential lenders (such as yourself) perceive the layout and content of loan applications currently active on the P2P market. Based on the loan information you are provided for the investment opportunity, you will decide whether to fund it or not, as well as how much to allocate. As a result, you may or may not spend the total $1,000 you have for the application. Any unused funds from the total of $1,000 you have been asked to administer will be invested in U.S. treasury securities due to market volatility and uncertainties of the economic recovery. As any other safe investment vehicle, treasury securities render lower returns than other riskier options.*

(cont): Instructions
LENDI –

Brings together ordinary people who need money for a variety of purposes or have some money they would like to invest. Loan applications are fulfilled through multiple lenders who are ***compensated proportionally to their contribution****. While Lendi is not responsible for loans that default, the site offers some information about each loan application to help lenders make better educated investment decisions.*

The information on each loan application includes ***total loan amount requested, loan purpose and maturity, interest rate, borrower credit rating****, as well as* ***either a generic image or a profile photo of the borrower****. Lendi determines the credit rating associated with each loan application using a statistical model that considers the borrower's official credit scores, income, and previous performance on the site.*

On the next screen, you are going to see ***a loan application randomly chosen by software from a large pool of applications****. As mentioned earlier, you can* ***spend up to $1,000 on the application****. You decide whether or not the application deserves funding and if so, how much you personally would give that particular applicant. So, you may end up allocating as little as $0, as much as $1,000, or any amount in-between.*

Appendix 3

Loan Application Sample. Icon sample is set to have been active for lender bids for 7 days out of the 14-day bidding period.

Loan Amount Requested	$10,000
Credit Rating	Above Average
Loan Repayment Period	5 years
Annual Interest Rate	10%
Loan Purpose	Small Business Development
Loan Percentage Already Funded	50%
Bidding Days Used	2 (vs 11) days

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