ESSAYS ON TRUST AND ONLINE PEER-TO-PEER MARKETS

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List of Abbreviations

AIC	Aikaike Information Criterion
BA	Business angel
B2B	Business-to-business
B2C	Business-to-consumer
BMBF	Federal Ministry of Education and Research
BTC	Bitcoin Cryptocurrency
CE	CrowdEquity (meta case)
CF	Crowdfunding
CIP	Crowd investing platform
CMC	Computer-mediated-communication
CPI	Corruption Perception Index
DTI	Debt-to-income ratio
EB	EduPlayBox (case)
ECU	Experimental currency unit
FA	FeedApp (case)
GLOBE	Global Leadership and Organizational Behavior Effectiveness
IDT	Interpersonal Deception Theory
IS	Information systems
JOBS	Jumpstart our Business Startups Act
LIWC	Linguistic Analysis and Word Count
OLS	Ordinary least squares
PH	(Cox) Proportional hazards
P2P	Peer-to-peer
PG	Public good
PR	Public relations
SBA	Small Business Administration (US)
SD	Standard deviation
SME	Small and medium sized enterprise
SS	SimpleServ (case)
Somer’s D	Somer’s Delta
USP	Unique selling proposition
VC	Venture capital
VCM	Voluntary contribution mechanism
VHB	German Academic Association for Business Research
VIF	Variance inflation factor
WC	Word count

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1. Introduction

1.1 Relevance and Background

"While technology is important, it is what we do with it that matters."
Mohammed Yunus (founder of Grameen Bank, India)

The internet has led to the rapid emergence of new organizational forms such as the sharing economy, crowdfunding and crowdlending and those based on the blockchain (particularly, cryptocurrency trading). These new forms struggle for survival and need to gain the acceptance of a significant public user base and state bodies upon which they depend for their continued existence. At the same time, such novel online-intermediated markets present challenges to society. Particularly in early phases of adoption and diffusion, proponents of these organizational forms must overcome strong distrust from all sides – the public, the private sector and potential regulating bodies are all understandably skeptical of such developments as these bring with them not only promises but are often accompanied by Schumpeterian processes of creative destruction (e.g. Schumpeter, 1942) which threaten incumbent firms and related employment. Consider how taxi companies and their drivers worldwide have been affected by the ride-sharing firm Uber, or how local and even global hotel business owners and managers struggle to cope with the apartment-sharing venture AirBnB, both classical examples of the sharing economy. At the same time, both business models promise to lower the costs of local transportation and accommodation for consumers by breaking up hitherto state-sanctioned oligopolies (e.g. the famously expensive taxi medallions in New York City or the typically coordinated pricing strategies of hotel chains[1]). In early adoption phases of a new industry,

[1] See Baum & Mudamby, 1995; Kalnins, 2006;

typically both cognitive legitimation and socio-political legitimation are lacking (e.g. Aldrich & Fiol, 1994). Thus, the recurring question in management science (and economics) as to which new industries will ultimately be accepted by society (and the market) depends on a large number of conditions. A central phenomenon underlying the legitimacy of such new organizational forms is trust, which implies important roles not only for entrepreneurs and early adopters in these emerging markets but also for legislators, who must ultimately decide to which degree which types of regulation make sense at which time given economic and socio-political goals.

Therefore, in this work, I examine a number of these new organizational forms - crowdfunding, crowdlending and cryptocurrency (Bitcoin) trading in four empirical studies, that highlight particular facets of trust and how trust (or the lack thereof) can hamper or facilitate the diffusion of such models. While the first two empirical studies examine trust in two forms of crowdfunding - crowdlending and equity crowdfunding through a decision-making lens, the third presents an experiment on the role of trust in groups in cross-cultural comparison and the final empirical study explores the role of trust, corruption and institutional context in the global diffusion of Bitcoins.

Trust requires both exchange partners and interaction between them (i.e. some form of communication). Further trust requires at least one exchange partner to make him or herself vulnerable to the counterpart and thus expose himself to risk, e.g. of deception or betrayal (e.g. Venkataraman, 1997)[2]. Thus the agent's decision to expose himself to the risk of opportunistic action by another implies the presence of trust (Coleman, 1990; Furlong, 1996). Trust between team members can lead to commitment to the organization, improved perceived task performance and team satisfaction (Costa, 2003). Trust has also been found to promote cooperation and truth-telling propensity (Porta, Lopez-De-Silane, Shleifer, & Vishny, 1996).

[2] The economics literature defines trust as "making yourself vulnerable to another agent, whose [potentially opportunistic] behavior is not under your control" (Furlong, 1996, p. 7).

Similarly, it is well known that communication can promote trust as individuals get to know each other and discover commonalities, e.g. aligned incentives, common intentions, interests or goals, or on the flipside common dislikes or outcomes that both parties aim to avoid (Ben-Ner & Putterman, 2009). In part, communication can reduce knowledge asymmetries between two or more parties. Also, trust-building is critical in the fight for legitimacy of a new venture or the establishment of a new market (e.g. Aldrich & Fiol, 1994).

This work begins with an examination of crowdfunding and crowdlending, particularly regarding the roles of trust-based legitimation and communication– a recurring theme of all four empirical studies presented. To explore the role of trustworthy communication in crowdlending[3], the first study examines deception on a leading German P2P-lending platform and analyzes whether and how deception cues in textual loan applications of borrowers are related to the risk of loan default. The second study aims to open the black box of investor decision-making in equity crowdfunding by qualitatively exploring the role of the entrepreneur's communication with the crowd in the investor's decision process of whether or not to (co-)fund a startup, particularly in terms of perceived signals of trustworthiness of the entrepreneur and perceived risks of the venture. The study also aims to answer a critical question for entrepreneurs in the crowd – how they can achieve a critical mass of supporters for their venture. The third study focuses on a specific setting within which trusting behavior occurs: interactions between representatives of groups. More specifically, the study experimentally explores the role of group representatives, particularly the willingness to trust a (in)group representative to invest in a public good on one's behalf as well as the degree to which this contribution behavior is replicated cross-nationally (comparing pre-play communication and resulting public good investment behavior over time in Germany and Japan). The fourth

[3] "Trustworthy" here typically means that lenders can trust borrowers to pay back loans on time (Duarte, Siegel, and Young 2009).

and final study examines the emergence of cryptocurrency trading in diverse market settings and in particular, the roles that institutional voids and perceived levels of trust and corruption play in determining trading volume in a particular country. To understand how these precise research topics emerged, in the following, research questions are developed in light of recent literature, after which the further structure of the thesis is described.

1.2 Research Questions

Next, we briefly summarize the most relevant publications that both motivate our chosen approach and our research questions in each empirical study.

While research on communication and trust in IT-intermediated settings has begun to explore crowdfunding and crowdlending (e.g. Ahlers, Cumming, Günther and Schweizer, 2015; Sonenschein, Herzenstein and Dholakia, 2011; Lukkarinen, Teich, Wallenius, & Wallenius, 2016), to date, only a small number of published papers analyze the relationship between narratives and P2P lending, two of which are briefly described here. First, Sonenshein, Herzenstein, and Dholakia (2011a) note that many borrowers in the crowd offer similar explanations ("social accounts")[4] for why they need a loan; explanations that are followed by an acknowledgement (of mistakes in the past) or a denial (when borrowers refute something about their past credit history) significantly predicts funding success, e.g. that the loan threshold was reached and therefore paid out[5]. The authors interpret this finding by arguing that these two types of constructed narratives evoke trustworthiness among lenders. In a follow-up article, Sonenshein, Herzenstein, and Dholakia (2011b) investigate the impact of identities (e.g., "*hard-working*") that borrowers create or attempt to portray for themselves in self-description texts,

[4] Accounts allow social actors to explain situations and events that are deviant or unanticipated (Scott & Lyman, 1968).

[5] Recall that in crowdlending, loans are usually only paid out, when the funding threshold is reached. This is also the case in rewards-based crowdfunding, but can differ by platform, however. Some platforms consider a project successfully funded if 90% of the desired amount is reached.

drawing on qualitative methodology. Looking for six identity claims in prospective borrower narratives (hardship, trustworthiness, hardworking, successful, moral and religious), the authors find a significant effect of identities on funding success, and in a follow-up analysis, on repayment success. Also, 84% of borrowers constructed one or more identities in their loan descriptions (Sonenshein, Herzenstein, and Dholakia, 2011b).

Both studies focus on the perspective of borrowers. Therefore, in the first study of this work, we take the point of view of lenders and evaluate whether or not cues in the language of borrowers can yield important insights on the successful payback of their loan (i.e., whether they default or repay successfully). Further, we take an interdisciplinary approach, borrowing insights and methods from criminalistics (e.g. Buller and Burgoon, 1996) and linguistics (e.g. Pennebaker, Booth and Francis, 2007). Based on a sample of over 3000 crowdfunded loans on a well-known German crowdlending platform, the first empirical study therefore aims to answer the following research question using the method of survival analysis (e.g. Allison, 2014)[6]:

RQ1: *Can the occurrence of deceptive cues in soft information of IT-mediated P2P lending project descriptions help explain (or even better predict) loan default?*

While answering this question sheds light on the role of deception in P2P lending, it only gives us limited insight into success criteria, especially of newer forms of crowdfunding. To our knowledge, only two studies research success factors of equity crowdfunding in particular (Ahlers, Cumming, Günther, & Schweizer, 2015; Lukkarinen, Teich, Wallenius, & Wallenius, 2016). First, Lukkarinen et al (2016) find that in Europe, pre-selection of startups by crowdfunding platforms as well as the utilization of public and private networks help determine success or failure (Lukkarinen et al., 2016). The research paper by Ahlers et al. (2015) finds that providing more detailed information about risks and retaining equity both act

[6] Paul Allison, Ph.D., one of the foremost experts on survival analysis, kindly provided several helpful hints for this study based on a survival analysis workshop conducted in Stockholm in 2016.

as signals that strongly impact the probability of successful equity crowdfunding. Social capital, on the other hand, is found to have no significant effect on the probability of success, partly contradicting the first study. The authors call for research that further explores investment reasons in equity crowdfunding, pointing to limitations of their quantitative dataset (Ahlers et al., 2015). Neither of these studies focus on the decision-making processes underlying funding success criteria in an in-depth qualitative manner. Yet we seek to understand precisely how entrepreneurs can seek to build investor trust and legitimate their early-stage venture in the crowd.

To obtain a deeper understanding of what leads crowdfunding projects to a successful outcome, insights into the process of how individuals within the crowd reach their investment decisions are required. Based on this premise and three in-depth qualitative (interpretative) case studies of successful equity crowdfunding ventures, the second empirical study investigates the following research questions using theory-building from case studies methodology (e.g. (Corbin and Strauss, 1990; Eisenhardt, 1989):

RQ2a: *What roles do trust and perceived risk play in the decision-making process of crowd investors on CrowdEquity?*

RQ2b*: Further, how can these be influenced by founders and the platform?*

Up to this point, the research questions presented seek to explore the role of trust and communication in crowdlending and equity crowdfunding in Germany. However, this still leaves three central questions unaddressed – first, what do cultural differences suggest about the degree that trusting investment behavior should be replicated in other, very different national settings? Second, participation in donation and reward-based types of crowdfunding projects is often motivated not only by profit maximization but also by social goals; therefore, it seems sensible to explore how ex-ante communication effects the willingness to trust others in the public good investment setting. Finally, due to the IT-mediated context of the platforms, investments in crowdfunding are relatively anonymous; this makes it particularly interesting to know whether people from or in certain cultures are more willing to trust strangers to act on their behalf. Also, under which conditions are group representatives perceived as legitimate to invest on behalf of members of the group?

Yuki´s (2003) framework for understanding group behavior in collectivist countries and Yamagishi´s structural trust model (Kuwabara et al., 2007; Yamagishi, Cook, & Watabe, 1998), lead us to expect differences in trust between individualistic and collectivistic countries towards strangers in general, but also in the effect of communication between representative and constituency on the cooperative behavior of representatives. Therefore, using a sample of 231 subjects we use experimental methods to compare public good contribution behavior of group representatives in Germany, a rather individualistic, European country, with that in Japan, the classical example of a collectivistic country (e.g. Hofstede and Hofstede, 2010) in treatments with and without (pre-play) communication. This leads us to posit the research questions:

RQ3a: *What are intercultural differences in negotiation behavior of (group) representatives who do not know each other and also do not know their constituency very well?*

RQ3b: *Specifically, do more individualistic (collectivistic) cultures facilitate placing trust in a stranger´s cooperativeness (e.g. willingness to contribute to a public good) and if so, how?*

Answering these questions promises to shed light on investment behavior in two very different countries with contrasting levels of generalized trust. Yet, we have so far largely disregarded the role of the country's level of development (e.g. developing countries). Institutional theory assumes that the emergence and development of new markets is strongly linked to the emergence and development of specific institutions and rules that shape this market (Padgett & Powell 2012). Institutions interact with organizations to play a key role in economic development (e.g. Peng & Heath, 1996) and in shaping the legitimacy[7] of markets (Bowen & Cleckq 2008; Doh et al, 2010). Spaces where such institutions are lacking are known as institutional voids[8] (Khanna and Palepu, 2000). Institutional voids can inspire entrepreneurs to create or enter new markets (Mair & Marti 2009). Crowdfunding and cryptocurrency trading are good examples of such markets. But at the same time, a lack of financial (and technological) infrastructure can hamper entrepreneurs from entering such markets. This type of setting famously motivated Google executives to bring the internet to Sub-Saharan Africa with a network of hot air balloons and Facebook executives to attempt a similar feat with drones as of 2014, both strategic moves to allow their businesses and brands to expand further globally.[9] We also know that trust-based relationships can fill institutional voids, shaping performance particularly in the high-tech sector of emerging markets (e.g. Miller et al, 2009).

Yet little is known about how the absence of institutions may impact the attractiveness of the development of contested new markets such as crowdfunding and more recently, cryptocurrency trading. Similarly, markets with weaker institutions are often perceived as hotbeds for corruption (e.g. Luiz and Stewart, 2014), a phenomenon related to generalized trust (e.g. Uslaner, 2004; Rothstein, 2013); but at the same time, corruption (particularly in the form of bribes) can smooth business transactions in some markets. Both perceived trust and corruption are likely to impact the perceived legitimacy of new and contested markets (e.g. Miller et al, 2009; Anokhin and Schulze, 2009; Tonoyan et al, 2010). Finally, research on cryptocurrencies cryptocurrencies and trust is scarce and is sofar largely the domain of legal scholars (Nelms et al, 2018; Simser, 2015; Gruber, 2013). Therefore, in the fourth and final

[7] Legitimacy has been defined as "a psychological property of an authority, institution, or social arrangement that leads those connected to it to believe that it is appropriate, proper and just" (Tyler, 2006). See also Aldrich & Fiol (2004: 648) who differentiate between cognitive legitimacy ("knowledge about the new activity and what is needed to succeed in an industry") and socio-political legitimacy ("the value placed on an activity by cultural norms and political authorities").

[8] More formally, institutional voids have been defined as "a relative lack of intermediary firms, regulatory systems and contract-enforcing mechanisms" (Khanna and Palepu 2000; Khanna and Rivkin 2001).

[9] https://www.technologyreview.com/s/525951/facebooks-drones-will-battle-googles-balloons-to-spread-internet-access/

study, we therefore analyze the growth of the market for Bitcoin trading in 46 different countries over the time-period from 2013-2017 using Random Effects GLS regression (e.g. Laird 1982 & Ware, 1982; Diggle et al, 2002) and seek to answer the following research questions:

RQ4a: *What is the role of institutional voids in shaping the early market for cryptocurrency (Bitcoin) trading?*

RQ4b: *What roles do differing (perceived) levels of trust and corruption play in this development?*

Taken together, these research questions promise to shed light on the roles of trust, communication and context in online-intermediated transactions. Next, the structure of thesis is laid out.

1.3 The Structure of the Thesis

The dissertation is structured as follows: subsequent to the introduction, four individual, empirical research studies are presented. The first research study, written in collaboration with Dr. Dennis Steininger, Prof. Dr. Michael Woywode and Prof. Dr. Daniel Veit, is presented in chapter two. It has been submitted to the Journal of Information Technology (VHB: A). Based on a sample of over 3000 loans from a leading German crowdlending platform, it examines deception in peer-to-peer lending and analyzes whether deception cues of borrowers are related to the risk of loan default. The objectives of the paper are: (1) to determine whether linguistic cues to deception can be detected using content analysis approaches suggested by criminalistics theory, (2) to find out whether soft information (particularly textual cues) can help improve prediction of the hazard of loan default above and beyond traditional hard information about loans (e.g. credit grade, interest rate and loan duration) and (3) to discuss potential implications for research in the study of trust and deception in entrepreneurship and information systems. More specifically, the study investigates empirically whether specific properties of loan description texts crafted by borrowers that are predicted by theory to be related to deception – quantity (i.e. length), expressivity (e.g. emotionality), immediacy (e.g. use of words related to time and places), complexity (e.g. punctuation and use of long words), formality (e.g. "Sir"), diversity (of vocabulary used)– are more frequently present in defaulting loans in comparison with loans that are paid back in full.

While the findings of the first empirical study do not definitively relate certain linguistic deception cues to deception on behalf of borrowers, they nevertheless strongly suggest that deception is present on the platform observed and demonstrate that less creditworthy borrowers use different writing styles that are detectable using pattern matching techniques grounded in linguistics and criminalistics theory. The study therefore helps us to understand how credit decisions are made on online platforms, particularly in crowdlending. Further, the results may serve as a blueprint for lenders to further develop borrower screening systems for creditworthiness and deception.

The second research study is presented in chapter three. It is co-authored with Dr. Dennis Steininger and has been submitted to the *Journal of Strategic Information Systems* and presented at the 2017 Academy of Management Conference in a paper development workshop. The study aims to open the black box of investor decision-making in equity crowdfunding. The research qualitatively explores the roles that trust, perceived risk and communication play in the investor's decision of whether or not to (co-)fund a startup based on the analysis of three highly successful cases from one of the largest German crowd-equity platforms. In-depth interviews were conducted with all relevant parties of each case: the entrepreneurs who sought financing, the investors (a.k.a. "backers") and the staff running the online platform. This effort constitutes a deep-dive into critical success factors driving funding decisions and is, to our best knowledge, one of the first studies to take this approach.

The findings of the second study reveal that the crowd is heterogeneous and that both rational and emotional signals can promote (or hinder) investment. The study suggests that how startups communicate in their investor pitch impacts both the diversity and quantity of investments received by investors in the crowd, hence influencing the perceived legitimacy of the venture. Similarly, proactively involving the media (or a PR agency) early on is a method used by particularly successful entrepreneurs in the crowd. The findings suggest that truly successful equity crowdfunding campaigns employ a holistic approach to investor communication that includes both sufficient details for the due diligence process that appeal to rational investors, and emotional appeals such as selling the entrepreneur's vision and giving the impression of approachability. Further, the cases analyzed show that both material and immaterial incentives as well as industry trends draw the crowd. Overall, the study contributes to an in-depth understanding of mechanisms in equity crowdfunding, particularly concerning the contextual boundary conditions for successful campaigns. Utilizing the proposed model, entrepreneurs can optimize their communication and behavior towards the crowd.

The fourth chapter presents the third empirical study. The study was written in collaboration with behavioral economist Prof. Dr. Christiane Schwieren (University of Heidelberg) and public goods researcher Prof. Dr. Yoshio Iida (Kyoto Sangyo University) and has been presented at (peer-reviewed) national and international conferences. The study examines the willingness to trust a group representative to invest on one's behalf as well as the degree to which this behavior can be replicated cross-nationally in controlled experimental settings. More precisely, the study finds that the in-group formation of teams (in-group) plays a key role in determining the willingness to trust a group representative in a modified public goods game. The study finds that in Japan conditional cooperation rates are lower overall than in Germany, which is probably because the Japanese need significantly more time to form reciprocal bonds than allotted in the experimental chat procedure. Higher trust in strangers leads to increased willingness to trust a group representative to invest on one's behalf in Germany, but less so in Japan, a culture in which reciprocal relationships are not usually established ad-hoc, but require extensive relationship building (e.g. Kuwabara et al, 2007; Yamagishi and Yamagishi, 1994; Yuki et al, 2005). More generally, the study demonstrates that there are cultural differences in behaviour of representatives of interacting groups that can be detected in the laboratory.

The study contributes to a better understanding of the role of trusting intermediaries to conditionally cooperate on investments in different cultural settings with implications for crowdfunding, since investors need to trust entrepreneurs (particularly social entrepreneurs) to act on behalf of the group of backers. Also, in some cases, crowdfunding platforms choose which (social) projects to invest in on behalf of backers, who invest in a set portfolio of projects (e.g. SeedInvest.com). Such time-efficient automatic investment distributes risk for crowdinvestors but nonetheless requires trusting the intermediary, something heavily impacted by online and often indirect communication. Finally, while crowd entrepreneurs often initially confine their activities to one country, many are looking to expand internationally, increasingly to Asia (Kromidha, 2015), an ongoing process which is partly driven by Chinese expatriates (Weidenbaum and Hughes, 1996; Zheng at al, 2014). Therefore, it is helpful for entrepreneurs and SME managers in the crowd to know what type of communication will evoke trust in which setting and which type of behaviour to look out for among platform participants that may signal deception or lack of trustworthiness.

The fourth and final empirical study is presented in chapter five. The study is written in collaboration with Prof. Dr. Suleika Bort (Chemnitz University of Technology) and has been recently submitted to (peer-reviewed) national and international conferences. Based on a full sample of Bitcoin trading transactions from coindance, a well-known global (decentralized) trading platform, it examines the development of the volume of cryptocurrency trading over the time-period from 2013-2017 in 46 countries and analyzes whether or not perceived trust and corruption and the level of institutional voids are related to trading volume in a given country. The objectives of the paper are: (1) to explore what enables a contested emerging industry to develop given different levels of institutional voids and (2) to examine the roles of perceived trust and corruption on the amount of the cryptocurrency trading.

The study finds that perception of corruption in a country is positively related to bitcoin trading volume while the level of perceived (generalized) trust is negatively related. Further, the study finds that a given country's emerging market status negatively impacts trading volume, as does any type of legal regulation. The study implies that people in countries with high levels of perceived corruption seem to use this perceived lack of government control to more frequently engage in new and contested markets; the findings therefore support profit-seeking and tax-evasion motives for participation. That trust is negatively related implies a further participation motive – to compensate for lack of societal trust. Cryptocurrencies are designed to facilitate disintermediated online transactions without requiring trust of the exchange partner. Also, overall, emerging markets seem to be more poorly positioned to quickly take advantage of rapidly emerging and contested digital markets like cryptocurrency trading.

The study contributes to a better understanding of how institutions and in particular the absence of institutions (i.e., institutional voids), perceived trust and corruption impact the digital market frontier and suggests that government intervention at early stages of new markets hamper market activity and growth – in the case of Bitcoins, this seems true whether the government declares the currency as legal or restricted. Those markets seem to fare best from a growth perspective, which remain unregulated. From the perspective of cognitive legitimacy (e.g. Aldrich & Fiol, 1994), both knowledge about Bitcoin trading and what it takes to succeed in this new industry have clearly grown over the time-period of observation, increasing legitimacy of the industry. Also, cryptocurrencies present an example of how technology can help fill both institutional voids (e.g. in Sub-Saharan Africa) and “trust voids”, e.g. in countries in which general societal trust is low, therefore taking a compensatory role. At the same time, the technology can be misused to facilitate illicit activities such as money laundering and tax evasion with possible detrimental effects on socio-political legitimation. Therefore, further study is needed.

1.4 References (Introduction)

Ahlers, G. K., Cumming, D., Günther, C., & Schweizer, D. (2015). Signaling in equity crowdfunding. *Entrepreneurship Theory and Practice*, *39*(4), 955-980.

Aldrich, H. E., & Fiol, C. M. (1994). Fools rush in? The institutional context of industry creation. *Academy of Management Review*, *19*(4), 645-670.

Allison, P. D. (2009). Fixed Effects Regression Models SAGE Thousand Oaks.

Anokhin, S., & Schulze, W. S. (2009). Entrepreneurship, innovation, and corruption. *Journal of business venturing*, *24*(5), 465-476.

Baum, T., & Mudambi, R. (1995). An empirical analysis of oligopolistic hotel pricing. *Annals of tourism research*, *22*(3), 501-516.

Ben-Ner, A., & Putterman, L. (2009). Trust, communication and contracts: An experiment. *Journal of Economic Behavior & Organization, 70*(1), 106-121.

Bowen, H. P., & De Clercq, D. (2008). Institutional context and the allocation of entrepreneurial effort. *Journal of International Business Studies*, *39*(4), 747-767.

Buller, D. B., and Burgoon, J. K. 1996. "Interpersonal deception theory," *Communication Theory* (6:3), pp. 203–242.

Coleman, J. S. (1990). Relations of trust. *Foundations of Social Theory, Cambridge, London*, 91-116.

Costa, A. C. (2003). Work team trust and effectiveness. *Personnel Review, 32*(5), 605-622.

Diggle, Peter J.; Heagerty, Patrick; Liang, Kung-Yee; Zeger, Scott L. (2002). *Analysis of Longitudinal Data* (2nd ed.). Oxford University Press. pp. 169–171.

Doh, J. P., Howton, S. D., Howton, S. W., & Siegel, D. S. (2010). Does the market respond to an endorsement of social responsibility? The role of institutions, information, and legitimacy. *Journal of Management*, *36*(6), 1461-1485.

Eisenhardt, K. M. (1989). Building theories from case study research. *Academy of management review*, *14*(4), 532-550.

Furlong, D. (1996). The Conceptualization of 'Trust' in Economic Thought.

Gruber, S. (2013). Trust, Identity and Disclosure: Are Bitcoin Exchanges the Next Virtual Havens for Money Laundering and Tax Evasion. *Quinnipiac L. Rev.*, *32*, 135.

Hofstede, G., Hofstede, G. J., & Minkov, M., 2010. *Cultures and Organizations: Software of the Mind* (3rd ed.). New York, NY: McGraw-Hill.

Kalnins, A. (2006). Markets: The U.S. lodging industry [Electronic version]. Journal of Economic Perspectives, 20 (4), 203-218.

Khanna, T., Palepu, K., 2000. The future of business groups in emerging markets: long-run evidence from Chile. *Academy of Management Journal* 43 (3), 268–285.

Khanna, T., Rivkin, J.W., 2001. Estimating the performance effects of business groups in emerging markets. *Strategic Management Journal* 22 (1), 45–74.

Kromidha, E. (2015, November). A comparative analysis of online crowdfunding platforms in USA, Europe and Asia. In *eChallenges e-2015 Conference, 2015* (pp. 1-6). IEEE.

Kuwabara, K., Willer, R., Macy, M. W., Mashima, R., Terai, S., & Yamagishi, T. (2007). Culture, identity, and structure in social exchange: A web-based trust experiment in t the United States and Japan. *Social Psychology Quarterly*, *70*(4), 461-479.

Laird, Nan M.; Ware, James H. (1982). "Random-Effects Models for Longitudinal Data". *Biometrics*. 38 (4): 963–974.

Luiz, J. M., & Stewart, C. (2014). Corruption, South African multinational enterprises and institutions in Africa. *Journal of Business Ethics*, *124*(3), 383-398.

Lukkarinen, A., Teich, J. E., Wallenius, H., & Wallenius, J. (2016). Success drivers of online equity crowdfunding campaigns. *Decision Support Systems*, *87*, 26-38.

Mair, J., & Marti, I. (2009). Entrepreneurship in and around institutional voids: A case study from Bangladesh. *Journal of Business Venturing*, 24(5), 419-435.

Miller, D., Lee, J., Chang, S., & Le Breton-Miller, I. (2009). Filling the institutional void: The social behavior and performance of family vs non-family technology firms in emerging markets. *Journal of International Business Studies*, *40*(5), 802-817.

Nelms, T. C., Maurer, B., Swartz, L., & Mainwaring, S. (2018). Social payments: Innovation, trust, Bitcoin, and the sharing economy. *Theory, Culture & Society*, *35*(3), 13-33.

Padgett, J. F., & Powell, W. W. (2012). The emergence of organizations and markets. Princeton Univ. Press.

Peng, M. W., & Heath, P. S. (1996). The growth of the firm in planned economies in transition: Institutions, organizations, and strategic choice. *Academy of management review*, *21*(2), 492-528.

Pennebaker, J. W., Booth, R. J., & Francis, M. E. (2007). Linguistic inquiry and word count: LIWC [Computer software]. *Austin, TX: liwc. net.*

Porta, R. L., Lopez-De-Silane, F., Shleifer, A., & Vishny, R. W. (1996). *Trust in large organizations* (w5864). Retrieved from http://scholar.harvard.edu/files/shleifer/files/trust.pdf

Qian, X., & Ukkusuri, S. V. (2017). Taxi market equilibrium with third-party hailing service. *Transportation Research Part B: Methodological*, *100*, 43-63.

Rothstein, B. (2013). Corruption and social trust: Why the fish rots from the head down. *social research*, *80*(4), 1009-1032.

Schumpeter, J. (1942). Creative destruction. *Capitalism, socialism and democracy*, *825*, 82-85.

Simser, J. (2015). Bitcoin and modern alchemy: in code we trust. *Journal of Financial Crime*, *22*(2), 156-169.

Sonenshein, S., Herzenstein, M., & Dholakia, U. M. (2011). How accounts shape lending decisions through fostering perceived trustworthiness. *Organizational Behavior and Human Decision Processes*, *115*(1), 69-84.

Tonoyan, V., Strohmeyer, R., Habib, M., & Perlitz, M. (2010). Corruption and entrepreneurship: How formal and informal institutions shape small firm behavior in transition and mature market economies. *Entrepreneurship theory and practice*, *34*(5), 803-832.

Tyler, T. R. (2006). Psychological perspectives on legitimacy and legitimation. *Annu. Rev. Psychol.*, *57*, 375-400.

Uslaner, E. M. (2004). Trust and corruption. In *The new institutional economics of corruption*, 90-106). Routledge.

Venkataraman, S. (1997). The distinctive domain of entrepreneurship research. *Advances in entrepreneurship, firm emergence and growth*, *3*(1), 119-138.

Weidenbaum, M. L., & Hughes, S. (1996). *The bamboo network: How expatriate Chinese entrepreneurs are creating a new economic superpower in Asia*. Simon and Schuster.

Yamagishi, T., Cook, K. S., & Watabe, M., 1998. "Uncertainty, Trust, and Commitment Formation in the United States and Japan." *American Journal of Sociology, 104*(1), AJSv104, 165-194.

Yamagishi, T., & Yamagishi, M. (1994). Trust and commitment in the United States and Japan. *Motivation and emotion*, *18*(2), 129-166.

Yuki, M. (2003). Intergroup comparison versus intragroup relationships: A cross-cultural examination of social identity theory in North American and East Asian cultural contexts. *Social Psychology Quarterly*, 166-183.

Yuki, M., Maddux, W. W., Brewer, M. B., & Takemura, K. (2005). Cross-cultural differences in relationship-and group-based trust. *Personality and Social Psychology Bulletin*, *31*(1), 48-62.

Zheng, H., Li, D., Wu, J., & Xu, Y. (2014). The role of multidimensional social capital in crowdfunding: A comparative study in China and US. *Information & Management*, *51*(4), 488-496.

2. Leveraging the Value of Soft Information for Peer-to-Peer Lending Platforms: A Study of Linguistic Cues

Abstract: Many credit decisions are now made on online platforms (e.g., in P2P lending). Impersonal communication in this context lowers the costs of lying and incentivizes borrowers to misrepresent their creditworthiness in order to improve credit conditions. However, simultaneously, these platforms generate a plethora of soft information such as personal profiles or communication data which enable new algorithms to better detect risky borrowers. Based on these notions and criminalistics theory, we develop a linguistic content analysis process to improve default detection in P2P lending, enabling platforms to improve their design to facilitate investor decisions and identify fraudulent lenders. To evaluate our approach, we combine traditional hard lending information (e.g., lending amount, interest rate, default risk) and linguistic artefacts of deceptive language (i.e., soft information) from a sample of 3661 loan profiles on a popular crowdlending platform. Our results indicate that the approach taken can significantly improve default risk evaluation compared to classic approaches using only traditional hard lending information. Our results relate linguistic cues to economic transaction outcomes and interpret them in light of agency and interpersonal deception theory. We find that the linguistic deception cues of quantity, diversity, complexity, expressivity, and immediacy in loan descriptions are significantly positively related to the hazard of loan default by borrowers, while use of positive affect reduces the hazard. This demonstrates that soft information can be used to better detect risky P2P lending profiles, leading to potentially higher professionalism and profitability for both P2P lending firms and lenders as well as higher platform adoption rates.

Keywords: Crowdfunding, Peer-to-Peer Lending, crowd lending, default risk, content analysis, decision making, linguistic cues, interpersonal deception theory, computer linguistics

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2.1 Introduction

Peer-to-peer (also P2P, person-to-person, crowd or social) lending allows private lenders to issue smaller loans to borrowers via an online platform without the need to directly engage with traditional banks. Private lenders each provide small sums until the target amount is reached and the loan is granted (the crowdfunding principle). One such firm and the subject of our study is *PeerCo*[10], a large German P2P lending platform. While lenders are attracted by relatively high rates of return, borrowers typically resort to P2P lending when they want a loan quickly without facing complex bureaucratic hurdles and screening by traditional banks. Declared a breakthrough business idea in the Harvard Business Review in 2009 (Benyus et al. 2009), the P2P lending market has grown rapidly. Global crowdfunding volume (mainly P2P lending) exceeded $34 billion in 2015 and increased over 1000 percent in three years. It is expected to grow to $300 billion in 2025 (Hogue 2015; Massolution 2013; World Bank 2013).

P2P technology has continued to enable fundamental changes in the financial sector (Wang et al. 2009) and beyond. However, crowdfunding and particularly P2P platforms face several challenges in platform design and incentive alignment between exchange partners (Bretschneider and Leimeister 2017; Burtch et al. 2018; Feller et al. 2017; Thies et al. 2016; Wessel et al. 2017). First, investors on these platforms are mainly amateurs who are easily influenced by many non-traditional factors surrounding the investment offering. Examples include the borrowers' characteristics such as gender, age or their language when describing the need for a loan (Hoegen et al. 2017). Secondly, borrowers may turn to P2P platforms when they experience difficulties receiving loans elsewhere potentially leading to adverse selection in P2P lending markets. Here, adverse selection means that borrowers who privately know they want to finance high risk projects have higher incentives to participate in such P2P markets

[10] Name anonymized as agreed with the firm.

compared to borrowers who search for financing for average risk projects (Akerlof 1970). Third, fraud in P2P lending markets presents a substantial problem. Thus lenders are confronted not only with adverse selection due to information about the borrower's true risk being privately held, but also with moral hazard – the risk that borrowers will not use the funds in the way they promised. Overcoming fraud issues is seen as central to the success or failure of P2P lending platforms (Knowledge@Wharton 2017). Share prices for LendingClub, the largest P2P lending platform, recently dropped by half (TechCrunch 2016) under scrutiny from the California Department of Business Oversight[11]. LendingClub apparently misrepresented its default rate to consumers as 4-6% when it was actually 7-8% (Bloomberg 2016).

A defining characteristic of p2p lending platforms is that they fill the niche of providing small and fast loans left vacant by classical loan providers that typically focus on loans with much larger amounts (Burtch et al. 2014). While auditor training has been shown to be significantly linked to successful fraud detection (Drogalas et al. 2017), p2p lending platforms oftentimes lack the highly formalized underwriting controls of classical lenders and due to smaller staff size than traditional banks and therefore highly reliant on information systems to assist them in carrying out such screening and monitoring activities. For example, for the period from July 13, 2009 to September 30, 2015, the platform Prosper.com verified employment and/or income on only about 59% of borrower loans and about 73% of originations, while 13% of loan applications were cancelled due to inaccurate or insufficient employment or income information (Prosper 2016). This demonstrates that so far little verification/due diligence is being done on borrowers' creditworthiness.

[11] In the U.S., P2P lending is overseen nationally by the SEC, the CFPB and in some cases the FTC. The FDIC, which insures bank accounts up to $100k, applies only to traditional banks, a loophole for P2P lending that leads to higher risk for borrowers. In Germany, this role is taken by the German Financial Supervisory Authority (BaFin). According to a new law (the Kleinanlegerschutzgesetz or small investor protection law) from 2015, such platforms must file a prospectus and as of 2017, consumer protections as well as a self-disclosure mandate of income-related information for borrowers took effect.

While statistics and recent studies speak for themselves, P2P lending is also unique in that, unlike deception in online dating (where individuals meet face-to-face and risk being publicly shamed), deceptive borrowers in this largely anonymous and disembodied setting face few or no social sanctions, especially in one-shot transactions. Research suggests that lack of physicality increases the opportunities for deception (Toma and Hancock 2010), which has made online deception research highly interesting for IS researchers (Ho et al. 2016; Ludwig et al. 2016; Proudfoot et al. 2016; Siering et al. 2016; Zhang et al. 2016).

This paper is motivated by a problem inherent to P2P lending: platform lenders need to decide whether or not to lend solely on lean information provided on the platform about the borrower such as financials (e.g., the interest rate) and textual project descriptions on a website. This differs from other platforms; for instance, in reward-based crowdfunding (e.g., Kickstarter) further information is commonly provided in the form of videos. The absence of this type of information on P2P lending platforms excludes intimate personal information that could otherwise increase borrower accountability and lender trust. Experiments with cheap talk (e.g. unverifiable communication that does not directly affect who gets what) show that individuals pay greater attention to more credible signals (Crawford and Sobel 1982; Farrell and Rabin 1996). Many researchers suggest that the incapability of private lenders to decide on trust- and creditworthiness ex-ante puts the p2p-business model at risk (Hoegen et al. 2017) and a is a problem that needs to be resolved. In the absence of professional screening by a third party, borrowers are tempted to present facts in an overly optimistic way (signaling) or to deceive in order to increase their *funding success* (i.e., the credit is issued because sufficient lenders provide money to reach the requested amount). Recent experimental evidence in IS shows that certain language-action cues (e.g., cognitive load, affective process and wordiness) can reveal patterns of information behavior manifested by deceivers in spontaneous online communication (Ho et al. 2016). Literature also suggests that the ignorance or misinterpretation of relevant publicly available information is a frequent reason for misevaluation (Hildebrand et al. 2017; Hirshleifer 2001; Mild et al. 2015).

Despite its importance, the assessment of the relationship between ex-ante borrower-provided data and default in online lending markets (whether a borrower fails to pay back the credit to the lenders completely as planned) has received only limited attention (Berger and Gleisner 2009; Gonzalez and Loureiro 2014; Iyer et al. 2015; Ravina 2008).

And, while recent articles on deception detection included studies that examine textual cues, none of these focus particularly on the interactions with lending (the closest is Siering et al, 2016, which looks at the related domain of crowdfunding). To the best of our knowledge, to date only a small number of published articles exist which analyze textual cues or narratives on P2P lending platforms. Two of these focus on predicting *funding success* via borrowers' classified types of descriptions of their financing needs (Sonenshein et al. 2011) or types of identity claims in the texts (Herzenstein et al. 2011). Hence, both papers take the perspective of a borrower. Further, some authors have begun to assess the predictive capacity of soft information on lending profitability by examining if borrower-provided texts comprise hints on creditworthiness that lenders overlook (Greiner and Wang 2010; Herzenstein et al. 2008; Larrimore et al. 2011; Moulton 2007).

Overall, most existing studies mainly take a borrower perspective and look at funding success instead of repayment. Furthermore, they do not systematically question motivations or incentives that cause the observed effects (Gao et al. 2017). To fill this gap, we discuss the incentives of high-risk borrowers (lemons) to falsely signal low-risk. Thus, high-risk borrowers might provide a false, overly optimistic, or misleading (and therefore deceptive) picture of their creditworthiness in their loan descriptions. From this backdrop, we approach our analysis using *interpersonal deception theory*, which is also used in criminalistics. The theory suggests that deception is "*imperfect strategic behavior*" (Buller and Burgoon 1996). Deceivers are likely to leave language artifacts or cues that can be detected when analyzing language style.

We take a lender perspective and evaluate on whether or not these cues in the language of borrowers on the p2p lending platform studied can yield important insights that can feed into the automated identification of high risk borrowers (e.g., via machine learning algorithms). We therefore aim to answer the following research question:

Can the occurrence of deceptive cues in soft information of IT-mediated P2P lending project descriptions help to explain (and predict) loan default?

To the best of our knowledge, this is one of the first studies to combine research on automated deception detection in a computer-mediated P2P context with the evaluation of economic transaction outcomes (Gao et al. 2017; Herzenstein et al. 2011; Larrimore et al. 2011). On the basis of the structuring foundations of agency theory (Akerlof 1970), we use 'soft' textual borrower descriptions and hard information such as the credit grade from 3661 loan projects of the P2P lending platform *PeerCo*. Computer-supported content analysis and Cox regressions are applied in order to evaluate the research question (Zhou et al. 2004a).

2.2 Theoretical Foundations and Hypotheses

P2P platforms are prone to information asymmetries. Information asymmetries arise when borrowers have more information about their ability and willingness to repay (i.e., their creditworthiness) than lenders. This type of market failure puts lenders at a disadvantage and effects their ability to set interest rates, a major concern in credit markets (Stiglitz and Weiss 1981). When lenders do not know the risk level of borrowers they cannot perfectly price loans and equilibrium outcomes become unlikely. Without further information, it is difficult for lenders to tell high-risk from low-risk borrowers, which is known as adverse selection (Akerlof

1970). This situation can be exploited by borrowers. Information asymmetries help explain why financial intermediaries exist (Campbell and Kracaw 1980; Leland and Pyle 1977; Myers and Majluf 1984).

Information can be dichotomized into hard and soft information. Hard information (e.g., borrowing amount, interest rate) is quantitative and easy to store and transmit, and has a relatively uniform (unambiguous) interpretation, while soft information (e.g., loan descriptions provided by loan seekers) is usually communicated in textual form (Stein 2002). Researchers have criticized mainstream studies for their narrow focus on "functionalist" hard information (Lodh and Gaffikin 1997; Roberts and Scapens 1985). In this study, we make use of both hard and soft information on the borrower and his/her proposed project. Depending on the informational context of text, soft information can be "hardened" by quantifying and storing parts of it in a meaningful way.

In order to better understand information asymmetries in P2P lending (i.e., when borrowers have more information than lenders about their creditworthiness) and the incentives for borrowers to use over-optimistic (or misleading) signaling, we draw on agency theory and interpersonal deception theory.

2.2.1 Agency Theory

Agency theory helps us understand situations in which one party has more information than the other; on our p2p lending platform, only the borrower knows his/her true risk and can choose what he/she discloses to lenders. More generally, agency theory (Akerlof 1970) conceptualizes goal conflicts between two partners in economic transactions (principal and agent) where bounded rationality (i.e., rationality of decision-makers is limited by their cognition, decision time, and available information), fears of opportunism and information asymmetries exist

(Milgrom and Roberts 1992). Agency theory maintains that when agents have more information, the principal (i.e., the lender) cannot ensure that the agent (i.e., the borrower) is acting in his/her best interest.

Evidence that agency is helpful in digital settings and platforms can be found particularly in IS studies (e.g., Dibbern et al. 2004; Pavlou et al. 2007) but also in related management literature (Lin et al. 2013). In agency relationships where lenders are the principals and borrowers are the agents, the agents may exploit their knowledge of their own high-risk of default and spend the money even though they know they cannot pay it back. The loss incurred by the principal in such a case is known as agency loss.

In traditional markets, mechanisms are in place to mitigate this problem; such financial intermediaries reduce information asymmetry between parties (and by extension agency loss) by providing detailed information about borrowers (e.g. their income and credit history) to lenders. Banks go beyond this by providing human agents who act as risk experts to screen potential borrowers face-to-face and foster trust relationships in order to smooth transactions and facilitate repayment (e.g., Moulton 2007). P2P platforms usually avoid such face-to-face interactions entirely for cost reasons. Banks also retain historical information on borrowers, something that is still scarce in online P2P lending. P2P lending sites profit by largely disintermediating bank agents (by semi-automating due diligence), focusing on hitherto underserved borrowers (e.g. those with smaller credit histories or in niche markets) and relying heavily on online information about borrowers, such as their self-reported information (Lee and Lee 2012), to help mitigate the lender's adverse selection problem. A recent study on the US P2P lending site Prosper finds that providing more information improves lender screening and dramatically reduces the default rate for high-risk loans, with little effect on low-risk loans (Miller 2015).

While agency theory presents us with a useful starting point from which to explore p2p lending platform dynamics, in order to investigate (potential) deception, we first need to understand the decision-making process of investors in the crowd, the value of borrower signals (e.g. in their project/loan descriptions), and the accuracy by which ex-ante hard information impacts loan default. Some pieces of the information consist of exogenously verified hard facts; others (i.e., soft information, such as the textual description of why a loan is needed) can be influenced by the borrower and thus represent purposeful signals which are often susceptible to deception since the lender is presented with little information concerning the truthfulness of the description on the p2p platform. In a study of the US credit market, hard information is found to be less accurate for low *credit grades*, where soft information explains up to 39 percent of risk, which indicates that soft facts are more important when hard information conveys a negative image of creditworthiness (Moulton 2007). In classical credit markets as well as p2p lending platforms, borrowers often try to mitigate the negative effects of exogenous hard information by changing endogenous hard information (e.g., adapting the *interest rate*) or by conveying a positive image by providing reassuring (possibly inaccurate, misleading or false) soft information (e.g. in their crowdfunding project description). This may be particularly true for high-risk borrowers who stand to gain the most in relative terms by means of persuasion tactics especially in digital settings (Iyer et al. 2009).

2.2.2 Soft Information and Deception

Deception is defined as "intentional control of information […] to create a false belief in the receiver" (Hancock 2007, p. 290; Zhou et al. 2008, p. 119). By controlling or misrepresenting information an image of a borrower's creditworthiness can be created that is higher than the true one with the ultimate goal of achieving funding success. The incentive to deceive depends on individually perceived costs and benefits (Hurkens and Kartik 2009). Potential benefits from deception depend on the accuracy of verifiable hard facts: the more risk that can still be explained by soft information, the more a borrower has the opportunity to differentiate by providing overly positive soft information. Relatively risky borrowers within a given risk category have a higher incentive to misrepresent themselves since higher potential benefits are to be expected.

The anonymous and digital setting but also the current design of most p2p platforms facilitate deception, not only in lending (Caspi and Gorsky 2006; Herzenstein et al. 2011; Horne et al. 2007; Larrimore et al. 2011; Utz 2005). The internet has increased "physical, psychological, cultural [and] social distance" (Jones 1991, p. 372) between transaction parties as well as between decision and effects. Roberts and Scapens (1985) argue that organizational accountability benefits greatly from regular face-to-face contact and reduced physical distance between parties. Accordingly, research suggests that anonymity and the reduction in personal communication have decreased mutual empathy (Logsdon and Patterson 2010) and increased ambiguity and uncertainty in message decoding due to the lack of nonverbal cues (Daft and Lengel 1986). These tendencies increase the ease of and incentives for engaging in deception (Joinson and Dietz-Uhler 2002; Logsdon and Patterson 2010, 2010).

Evidence of the prevalence of deception on online platforms can be found in a number of recent studies that observe deception in the form of 'fake' reviews (Luca and Zervas 2013; Mayzlin et al. 2014; Ott et al. 2011; Zhang et al. 2016). For example, Luca and Zervas (2013) find that 16% of restaurant reviews on Yelp are filtered out as fake or suspicious and that incentives to commit review fraud include weak reputation. A handful of papers on P2P lending are worth mentioning but do not analyze textual descriptions. Michels (2012) finds that unverifiable disclosures matter in P2P lending and lead to more lenders responding to a loan request. Iyer et al. (2015) study how non-expert individuals screen their peer's creditworthiness and find that such peers predict default with greater accuracy than with the credit score alone.

At the same time, p2p platforms have strong incentives to lower the access barriers to credit, as they earn interest on each loan and depend on a critical mass of users for media coverage and venture capital financing; by setting a low bar for access, platforms can facilitate deception and fraud. Researchers mostly agree that the main factors determining the costs of deception are the consequences, the proximity to the victim, and the societal view of a deception as fair or unfair (Jones 1991; McMahon and Harvey 2006).

We assume that, for borrowers with risky projects or weak intentions to repay the borrowed money (lemons), the benefits of lying exceed outweigh potential costs (e.g. of having one's account suspended by the platform) and that lying costs are generally low: it is difficult to establish a valid legal argument for discrepancies between default and the promises made in descriptions. This problem is strengthened by the sheer number of parties involved in peer-to-peer settings, which make it too costly to systematically check such assertions. This is the case not only for the P2P-Lending service, but also for individual lenders who (due to the relatively small amounts lent, often to a portfolio of projects) have only limited incentives to investigate individual false or misleading project descriptions or moral hazard on behalf of the borrower (e.g. that some borrowers may spend the money on other things than their project once the loan is approved). While online rating systems mitigate this problem for identifiable repeat offenders to some degree, such systems rely on hard information (e.g., offenses reported by other users, official bankruptcy procedures). Also, for most one-off borrowers, a degradation of the future credit score (e.g. FICO[12]) is unproblematic.

[12] FICO (Fair, Isaac and Company) is a data analytics company in California that provides the well-known US consumer credit ratings used when applying for credit cards, home mortgages or motor vehicle financing. Scores are between 300 and 850 with higher indicating less risk. The algorithm is based largely on a given person's debts and payment history and is explained here: "How Are Credit Scores Calculated? Learn What Affects Your Credit Score". myFICO.com. Retrieved 2018-06-06.

2.2.3 Interpersonal Deception Theory

The *interpersonal deception theory (IDT)* institutionalizes the detection of liars through their language style based on a set of linguistic constructs also used in criminalistics (Buller and Burgoon 1996). One strategy for managing the discomfort caused by lying (or information manipulation) is psychological distancing from the deception and its possible negative repercussions (DePaulo et al. 2003; Knapp and Comadena 1979).

Interpersonal deception theory (IDT) proposes that liars subconsciously stand out since their motives leave artifacts in their language (Buller and Burgoon 1996). IDT comprises 18 propositions (see Table 15 of the Appendix).[13] IDT therefore suggests that deception is "*imperfect strategic behavior*" which nonetheless requires mental effort (Buller and Burgoon 1996). The authors list four message characteristics that reflect strategic intent: (1) uncertainty and vagueness, (2) non-immediacy and withdrawal, (3) disassociation and (4) image- and relationship-protecting behavior (Buller and Burgoon 1996). IDT tests and meta-analyses have confirmed that liars manipulate clarity, relevance, association, truthfulness and completeness when communicating (Buller and Burgoon 1996; Burgoon et al. 1996; DePaulo et al. 2003). Additional 'leakage' signs of strategic behavior include frequent speech errors and increased speech hesitations (awkward pauses) due to the cognitive demands of fabricating an untruthful account (Buller and Burgoon 1996; Griffin 2006).

Zhou et al. summarize and define a number of linguistic constructs or cues of deceptive intent in written language which we adopt below in Table 1 (Zhou et al. 2004b).

[13] While IDT was conceptualized to explain deception in communication in the form of strategic moves and countermoves, the core findings apply to asynchronous text as well as can be seen in Table 15 in the appendix.

Table 1 Definition of Linguistics Constructs, Adopted from Zhou et al (2004a)

Construct	Definition of Construct
Quantity	The quantity of information the sender wants to convey
Expressivity	The degree to which the sender colors his writing
Affect	The degree to which the sender describes (positive) personal emotions in his writing
Quality	The degree to which the sender signals due diligence in his writing, e.g., by conducting a spellcheck
Immediacy	The degree to which the sender associates with the content of and the degree to which he clarifies his role or the role of a group he belongs to in his message
Uncertainty	The degree to which the language of the sender indicates ambiguousness, e.g., leaves it open to interpretation
Complexity	The level of syntactical structures used by the sender
Diversity	The degree to which the sender's writing is multi-faceted in wordings and expressions
Specificity	The degree to which the sender specifies location and time for the conveyed information

We provide a condensed overview of the findings of empirical studies on the effects of these constructs as they relate to linguistic deception detection using a concept matrix (Webster and Watson 2002) in Table 2. The empirical studies included are all based on linguistic cues since non-verbal cues are not available in online profiles (Toma and Hancock 2010).

The results of these studies suggest that liars display above-average expressivity, affect, quality and uncertainty in their language and below-average immediacy and diversity. Findings on quantity, complexity and specificity are mixed but a majority of the studies categorized find that liars display higher quantity while displaying more complexity and less specificity in their text.

Two moderating factors for effect and direction are typically differentiated: the medium (email vs. instant chat, etc.) and the mode (verbal vs. written). Carlson et al. (2004) integrated the *computer-mediated communication theory* and the *interpersonal deception theory*. The authors argue that linguistic features are well suited to detect deception in computer-mediated communication; because they are well documented as data in IS settings. The characteristics of a medium facilitate or prevent the occurrence of deception (e.g., capacity to store and edit text)

(Carlson et al. 2004). This indicates that P2P lending platforms can facilitate or pose challenges to deception by means of input shaping.

Table 2 Concept Matrix – Linguistic Deception Detection (Only Empirical Studies)

Author(s)	**Medium**	**Setting**	**Quantity**	**Expressivity**	**Pos. Affect**	**Neg. Affect**	**Quality**	**Uncertainty**	**Immediacy**	**Complexity**	**Diversity**	**Specificity**
Burgoon et al. (2003)	Audio, chat	Sync.	+#	+#	+#	+#	+		-	-*	-	-*
Zhou et al. (2003b)	Email	Async.	+*	+	+*	+*	+*		-	+	-*	-
Newman et al. (2003)	FtF1, essay	Both				+*			-*	-*		
Zhou et al. (2004a)	Email	Async.	+	+		(+)	+	+*	-*	-*	-#	-#
Hancock et al. (2004)	FtF	Sync.	-#	+	+	+			-*	-		
Zhou et al. (2004b)	Email	Async.	+*	+*		(+)	+*	+*	-*	-*	-*	-
Qin et al. (2005)	Text, audio, FtF	Both	-		-	-		+#	-*	-*	-*	-#
Zhou and Zhang (2006)	Chat (IM)	Sync.	+	+						+*		+
Zhou and Zhang (2008)	Email (SM2)	Async.	+*	+*	+*	+*	+*	+*	-*	-*	-*	
Hancock et al. (2007)	Email (SM)	Async.	+			+			-*			+*
Toma & Hancock (2010)	Dating profile	Async.	-*			+#			-*			
ten Brinke & Porter (2012)	Audio, FtF	Sync.	-*		+	+						
Mollick (2014)	Project Profile	Async.					+*					
Burns & Moffitt (2014)	Audio	Async.				-						-
Briscoe, Appling & Hayes (2014)	Chat (IM)	Sync.	+*				-*					
Ho et al. (2015)	Chat (IM)	Sync.			+	+			-*			
Ho et al. (2016)	Chat (IM)	Sync.	-*		+	+				+		
Ludwig et al. (2016)	Email (SM)	Async.		+*	+*							[14]

Deception is facilitated by the asynchronous nature of online communication – liars can edit as often as necessary (Hancock et al. 2007; Zhou et al. 2004b; Zhou and Zhang 2008). Since liars also need to persuade, they tend to use carefully crafted text and speech. This allows them to

[14] Another recent study examines suspended projects on Kickstarter using machine learning techniques (Siering et al., 2016), however, the authors neither study the context of P2P lending nor focus on creditworthiness. They also limit their analysis to a battery approach, leaving individual linguistic cues as a black box.

manipulate and convince others by using numerous arguments and rhetorical techniques (Hancock et al. 2007). At the same, time, they may attempt to control information and especially attempt to hold back information that might reveal them as a liar. Others find that liars may communicate in a less diverse manner since they lack real knowledge of the issue (Zhou et al. 2004b); this could lead to them writing less.

Overall, signalling theory would suggest that longer project descriptions offer more opportunities to reduce information asymmetries (e.g. to better inform investors) and therefore lengthy descriptions imply a more honest lender. Flowing from these arguments, we posit:

H1: Borrowers who exhibit a lower *quantity* of text in their loan descriptions have a higher hazard of loan default.

Liars typically do not access real memory and therefore have to fabricate a convincing story, a cognitively taxing process (Hancock et al. 2007; Zhou and Zhang 2008). This could lead prospective borrowers to use more diverse wording and unnecessarily complex sentence structures that would otherwise have been corrected. Further, lower language diversity (e.g. the use of fewer unique words) can be seen as a sign of the level of education of the corresponding borrower; lower education is typically associated with higher levels of default (Brüderl et al. 1992).

Additionally, literature suggests that deceivers trying to convince groups have a more complex and difficult task compared to the ones only trying to convince a single person. Their language therefore tends to be more complex to make adequate and convincing justifications addressing different parts of the group (Zhou and Zhang 2006). As language diversity (higher usage of unique words) is sometimes used as a proxy for (language) complexity, we expect these two measures to go hand in hand and posit that:

H2a: Borrowers who exhibit higher *diversity* in language in their textual loan descriptions have a higher hazard of loan default.

H2b: Borrowers who exhibit higher *complexity* in language in their textual loan descriptions have a higher hazard of loan default.

Findings from computer-mediated communication, Zhou et al. (2004b) suggest that on the internet, the physical (and psychological) distance between sender and receiver decreases negative emotions experienced when lying. Moreover, the ease of communication control and editability of messages provoke the persuasive intent to crowd out other goals. As a consequence of computer-mediation, deceivers would purposely also use more (instead of less) *expressivity* in their writing. In the context of P2P loans, prospective borrowers are thus tempted to color their loan descriptions by using more descriptive language (e.g., adjectives and adverbs) and by displaying positive emotions – more positive *affect* – in order to signal creditworthiness and provoke bids on their loans. Thus, in a recent conference paper, Mitra and Gilbert (2014) find that emotional phrases lead people to invest in Kickstarter projects, finding a key role for (emotional) persuasion. Nonetheless, when it comes to repaying the debt, the likelihood of repayment might be correlated with the affect and expressivity which is displayed in the loan related project description. Therefore we posit:

H3: Borrowers who exhibit higher (i.e., more) *affect* language in their textual loan descriptions have a higher hazard of loan default.

H4: Borrowers who exhibit higher *expressivity* in language in their textual loan descriptions have a higher hazard of loan default.

Typographic errors are a sign of low quality (or unprofessionally crafted text) and could easily be removed in asynchronous communication. Consider, for example, how frequently hastily crafted text messages from friends on cell phones contain sloppy spelling and grammar errors versus in the context of official emails written to higher ranking co-workers or managers. Deceivers have been previously shown to display more typographical errors than truth-tellers (Zhou and Zhang 2008). Liars also need time to fabricate a convincing narrative and seem less likely to write in a hasty fashion. Therefore, we posit that:

H5: Borrowers who exhibit lower *quality* (more typos) in language in their textual loan descriptions have a higher hazard of loan default.

Liars may also want to be vague in their statements to decrease the ex-post verifiability of their statements and thereby tend to use rather unspecific language (Zhou et al. 2004a, 2004b; Zhou and Zhang 2008). This could also be fostered by their ambition to avoid contradicting themselves. In addition, since liars need to fabricate their story, a cognitively challenging task, they may be uncertain whether their story is convincing or not, which in turn might be reflected in a more uncertain language or writing style. As a result, we expect that deceivers will use more ambiguous language overall and posit:

H6: Borrowers who exhibit higher *uncertainty* in their language in their textual loan descriptions have a higher hazard of loan default.

Following this line of argument, liars also do not want to provide too many details on specifics such as their place and location. This is due to the fact that giving such details might make these more verifiable and traceable. On the other hand, if a deceiver wants to provide such specifics, the task of fabricating a convincing and non-contradictory storyline becomes even more challenging. Not revealing specifics such as location could also be a sign of distancing oneself from potential lenders. Therefore, prospective high-risk borrowers seem likely to avoid mentioning such specifics that allow for identification (Zhou and Zhang 2008). Reformulated as hypotheses, we posit that:

H7: Borrowers who exhibit lower *specificity* in language in their textual loan descriptions have a higher hazard of loan default.

It has been found that liars also disassociate themselves from their lies to lower verifiability and the psychological costs of lying (Hancock et al. 2007; Zhou and Zhang 2008). Such disassociation decreases the psychological costs of lying, both the rather immediately experienced negative affect and the more gradual perceived social costs of lying (e.g., deceivers violate social norms of fairness and truth-telling that are common across cultures). We therefore posit:

H8: Borrowers who exhibit lower *immediacy* in language in their textual loan descriptions have a higher hazard of loan default.

In summary, we infer that the significant occurrence of deception constructs in a borrower's loan description suggests deceptive intent. Moreover, we propose that deceptive intent is an indicator for high default risk of the borrower since the benefits of lying are highest for lemons while we assume that costs are uniformly low for all borrowers due to the nature of the online medium. Since high true risk would result in a high hazard of loan default, in order to test our hypotheses, we analyze the relation between the frequency at which deceptive cues are used in loan descriptions and the loan's respective *hazard of default*.

2.3 Method

We analyze the textual descriptions (i.e., soft information) of loan projects from a leading German P2P lending platform for cues to deception and their impact on the hazard of loan default using survival analysis. We apply content analysis to transform text into measurable factors (Berelson 1952), following an established procedure (Insch et al. 1997) and deductively derive cues to deception from the literature for our coding scheme. Content analysis has several advantages. It enables the examination of rich communication data previously untapped by merely quantitative studies. Moreover, its observing perspective on communication (Barley et al. 1988) avoids the risk of influencing the behavior of borrowers, this risk is particularly a problem when directly surveying deceivers.

Validity can be divided into content (also called construct), convergent, discriminant and nomological validity (Homburg and Giering 1998; Insch et al. 1997). We ensure nomological validity by embedding the constructs in the *interpersonal deception theory*. We test for discriminant validity across constructs in multicollinearity pre-tests where we exclude irregularly cross-correlated categories (Morris 1994; Weber 1990). Finally, we aim to maximize content- and convergent validity through selecting coding categories from previous deception literature (Zhou et al. 2003a, 2004b).

2.4 Empirical Context, Data Collection, and Sample

PeerCo is a large German P2P lending platform founded in 2007. We chose *PeerCo* as our data source due to transparent lending processes and the availability of textual project descriptions from the borrowers for funded projects. Users become either a borrower or lender by providing a valid email address and then going through an identity verification process. They provide information such as address, identity card and bank account number. Borrowers then create loan requests which contain information about them and their request purpose. This information is summarized in their loan listing, including the amount requested, interest rate offered, loan duration, percentage financed so far, and open amount (see Figure 1). A disclaimer under each description reads "The user is responsible for the accuracy of the statements, for which *PeerCo* assumes no liability." All listings also contain an image and free-form text, where prospective borrowers describe themselves (e.g., signals of trustworthiness), why they require a loan and what they intend to do with it. When choosing whom to lend to and how much, lenders also see the borrower's credit rating, age, city of residence and self-reported occupation category (e.g., civil servant).

Figure 1 Sample Loan Description, anonymized[15]

To draw inferences from a sample of the population of *PeerCo* users, the sample needs to be appropriately sized to minimize both type I and type II errors (Petter et al. 2007). A ratio of 70:1 is considered to be appropriate (Maxwell 2000). For our 13 predictors, this would require

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[15] English Translation of Loan Description:

Title: "Move to Hamburg"
Text: "I am a commuter and drive 150 km every day to get to work ! I depend on my car because of rotating shift work and just had to buy a new one because the old one broke down. Since I have 400 € in costs for driving I want to move to Hamburg ! Would be really happy about your support ! I work at the city's port and it is a very well paid job but paying everything at once on my own is difficult ! I chose the premium [credit report] package so that lenders won't have problems in the worst case ! The great part about PeerCo is that private people help one another and earn money themselves without the banks ! Many thanks!"
Disclaimer: The user is responsible for the accuracy of the statements, for which PeerCo assumes no liability.

at least 910 observations.[16] We consider loans with 36 and 60 months duration respectively that were issued from 2007 through 2012. This resulted in 3661 observations. In addition, several hours of preparatory interviews with an executive at *PeerCo* were conducted to receive further information on our dataset and answer open questions about the specifics of the platform.

2.5 Operationalization of Measures

To support causation assumptions, we need to show '*association*' (correlation), '*isolation*' (rejection of alternative hypotheses) and '*temporal precedence*' for the relationship between the deception constructs and our dependent variable *default* (Cook and Campbell 1979; Gefen et al. 2000).[17]

Since borrowers compose their loan descriptions before they can default, temporal precedence is naturally established. We demonstrate association and isolation via content analysis and statistical tools (Shi and Tao 2008). We infer association from a correlation of our independent variables with the hazard of loan default.

Dependent variable: We model loan *default* as a binary variable (1=true, 0=false). We count loans as defaulted if parts of the loan were not paid back, not however if payments were simply late. In our analysis, we assume that deceptive intent is an inverse indicator of an individual's true ability to repay.

[16] We also conducted a power analysis using the software package G*Power 3.1, confirming that the sample size is adequate.

[17] We argue that lemons have a higher hazard of default but do not go so far as arguing that linguistic cues cause default. Instead, linguistic cues will be reflective of borrower ability to repay and noisily reflective of borrower intent to repay (as some borrowers may intend to repay without having the ability to do so).

Independent variables: For our correlation analysis, quantitative variables, such as the *credit grade* and *interest rate*, and qualitative constructs based on text, such as *quantity* and *expressivity*, are tested (see Tables 3 and 4 for operationalizations).

The linguistic deception measures are provided by the software LIWC (using the German LIWC dictionary), supplemented by a Visual Basic macro written to count typographical errors using the spellcheck() function of Microsoft Office and by custom Microsoft Excel functions employed to count punctuations, greetings and emoticons.

Table 3: Operationalization of Linguistic Deception Constructs, Adopted from Zhou et al. (2004a)

Construct	Definition of Construct	Selected Measures	Examples
Quantity	The quantity of information the sender wants to convey	Number of words	the, I, loan, going
Expressivity	The degree to which the sender colors his writing	Number of modifiers (adjectives, adverbs) Number of perceptual verbs	hot, small, incredibly, supposedly see, feel, hear, taste, touch
Affect	The degree to which the sender describes (positive) personal emotions in his writing	Number of positive affect words Emoticons	happy, love, good :) :-) :] :D ;D
Quality	The degree to which the sender conducts writing due diligence by proofreading, a signal of professionalism/quality	Number of typos (i.e., misspelled words) Absence of greeting	wll (will), gaol (goal) Hey! Hi guys,
Uncertainty	The degree to which the language of the sender indicates ambiguousness	Number of modal verbs Negation words	can, could, may, might, not, no, nor
Immediacy	The degree to which the sender associates with the content of and the degree to which he clarifies his role or the role of a group he belongs to in his message	Number of self-references, 1st Plural Pronouns	I, me, mine We, our, us
Complexity	The level of syntactical structures used by the sender	Pausality	...I mean...why should I pay more at a bank?
Diversity	The degree to which the sender's writing is multi-faceted in wordings and expressions	Unique words (i.e., non-repeated words in a set)	n/a
Specificity	The degree to which the sender specifies location and time for the conveyed information	Number of spatial specifications, Number of temporal specifications	up, down, above, below now, before, after, tomorrow

Table 4 Operationalization of Hard Variables

Variable	Operationalization	Type
Credit Grade[18]	A=1, B=2, C=3,…,H=8	Ordinal
Debt-to-income Ratio	Values 1-4, where 1=debt burden of <20 percent of income, 2=20-40%, 3=40-60%, 4=60-cap at 67%	Ordinal
Duration	36 or 60 (months)	Ordinal
Requested Amount	Provided as integer	Metric
Interest Rate	Provided as percentage	Metric
Gender	Categorical (male, female)	Binary
Age	Subdivision into age groups (<25,26-40,41-60, >61)	Ordinal
Occupation	Categorical (see appendix)	Ordinal

[18] The credit grade on this platform is proprietary but based largely on the borrower's credit rating as reported by the German ‚Schufa' service.

2.6 Analysis

Survival analysis is an appealing estimation technique for modeling time-dependent processes in our data for a number of reasons. First, a major benefit of survival analysis (particularly the Cox proportional hazards model) is that it does not rely on distributional assumptions. It can therefore deal with left and/or right censoring of the data. Furthermore, our dataset contains loans that were not yet completed at the time of analysis, which would be missing values in OLS regression. Using a Cox-hazard rate model specification (Cox 1972, 1975) these right-hand censored observations are included in the estimation. Finally, survival analysis particularly in the form of a Cox hazard rate specification has already been successfully applied to crowdfunding (Allison et al. 2015; Emekter et al. 2015; e.g., Kim and Viswanathan 2014; Li et al. 2016; Lin et al. 2013; Serrano-Cinca et al. 2015). For these reasons, we call upon survival analysis, which allows us to find factors that explain loan default, while predicting default probability based on linguistic constructs suggested by deception literature.

Our borrower default estimates are based on proportional hazard models in which the borrower's hazard of default is modelled as a multiplicative function of a common base-line hazard and a firm-specific component. Since the base-line hazard is estimated using a non-parametric technique while the latter component is modelled as a parameterized function of firm characteristics, this approach is often described as a semi-parametric estimation technique.

Three types of loans can be distinguished: those that default during the observation period, those that are finished without default in the observation period and, finally, those that are running and have not yet defaulted at the cutoff date (censoring date). We focus on defaulted loans. We estimate the standalone and joint effect of linguistic variables on our binary dependent variable loan default. We are thus interested in the influence of hard and soft information on the hazard of a 'loan default' event occurring. We estimate a function that predicts the hazard of default based on a linear combination of linguistic variables as well as classical borrowing risk related variables using a semi-parametric Cox proportional hazards (PH) regression model (Cox 1972).[19]

The Cox model is inherently robust, to the degree that it is often a good approximation, even when its assumption – proportional hazards (PH) – is violated (Allison 2014). The PH assumption is that the independent variables should be time-independent. Stated another way, the effect of each variable on the log of the hazard should be the same at all points in time (Allison 2014). We check this PH assumption using two methods (Box-Steffensmeier and Zorn 2001): First, we check if the Schoenfeld residuals of our explanatory variables are unrelated to survival time (Grambsch and Therneau 1994). Second, we incorporate time-dependent covariates by including interactions of our covariates with functions of time (*t*, *ln(t)* and t^2); to test each covariate individually we fit one model per covariate and function of time. In addition, we fit one model including all covariates as a joint test (Model 3). The results suggest that three of our variables violate the PH assumption of the standard model. As suggested in literature, we therefore extend the standard model for time-varying covariates (see Appendix for details).

The final specifications for Model 1 are given in equation (1). The hazard of default for a borrower *i* belonging to group *j* at time t is given by the (exponentiated) vector of signals $S_{i,t}$, hard information $H_{i,t}$ and linguistic categories $C_{i,t}$. $S_{i,t}$ includes the loan amount in Euros, the interest rate in percent, the number of bids in 250€ increments and the loan duration in months. $H_{i,t}$ encompasses the loan grade ranging from 1-8 (lower is better) and individual *i*'s debt-to-income (dti) ratio ranging from 1-4 (1: 0-20%, 2: 20-40%, 3: 40-60%,4: >60%, lower is better).

$$h_i(t) = h_0(t)\exp\left(\beta_1 S_{i,t} + \beta_2 H_{i,t} + \beta_3 C_{i,t}\right) \qquad (1)$$

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[19] See Appendix for mathematical notation details.

where h_0 denotes the baseline hazard, the betas denote the estimated coefficients of variables $S_{i,t}$, $H_{i,t}$ and $C_{i,t}$ and the subscript "i,t" indicates a time-varying measure of our covariates (here only the variables interest-rate, loan-grade and dti-ratio display time-varying effects).

Our data showed signs of both multicollinearity and heteroskedasticity (Breusch and Pagan 1979). Since 93% of borrowers do not default, the distribution of the dependent variable (*default*) in our final sample is strongly skewed towards the upper boundary. These characteristics lead to inaccuracies when using an OLS regression (Gefen and Rigdon 2011) or SEM (Gefen et al. 2000).

We first test for multicollinearity, also to verify the empirical discriminant validity of our independent variables. The usual measures for multicollinearity include the *variance inflation factor* (VIF) and the *condition number* for the independent variables (Baum 2006; O'Brien 2007). The VIF measures the degree to which the variance of an estimated regression coefficient is increased (or inflated) by collinearity (i.e., when two predictor variables in a regression are correlated).

To improve model fit, we remove those variables with highly insignificant p-values (above our cutoff of p=.025) and with a high variable inflation factor (VIF), designated as having a value above 10 as suggested (Kennedy 2008; Kutner et al. 2004).

We are left with 13 predictor variables, yielding Model 2, which include our three main hard facts from Model 1 as well as the loan amount, the number of bids on each loan, and eight soft factors[20] based on each individual's loan description. Model 2 gives a condition number of 17.02 and all VIF values are significantly below the threshold of 10, indicating that the model

[20] Greeting included, negation words, modal verbs, modifiers, positive affect words, positive emoticons, temporal and spatial words

is free of collinearity. We compare goodness-of-fit between Model 1 and our reduced Model 2 using two criteria: the Akaike information criterion (AIC) and the log likelihood (Akaike 1974).

We introduce robustness tests which ensure that our results are not provoked by omitted-variable bias, fixed effects, or model misspecification. Regarding the establishment of causality, the tests are supposed to isolate deception as an indicator of high risk which causes the default (Cook and Campbell 1979).

Model 3 is the same as Model 2, except that it adds demographic control variables (e.g., age, gender, occupation, borrower's home state[21]) to the model, represented by an additional vector $\beta_i D_{i,t}$ (D for demographic).

To test the value of soft information beyond that of the hard facts of a borrower's given loan on the platform, we need a measure of the variance that is *not* explained by hard information. However, for our survival analysis model, we cannot use the standard coefficient of determination (R^2) because it only applies to OLS models (Zheng and Agresti 2000). We therefore apply Somer's D rank correlation (often referred to as pseudo-R squared) as an alternative goodness-of-fit test (and measure of variance) to measure explanatory and predictive capability as suggested in the literature (Somers 1962). Somers' D measures how much the prediction for the dependent variable improves, by including an independent variable. More formally, it measures the ordinal association of random variables and is based on calculating the percentage of concordant or "matching" pairs, see also Newson (2002, 2006).[22]

[21] The variable *female* was coded 1 if true and 0 if false. The *home state* variable takes is a categorical variable with a category for each of 16 German states (*Bundesländer*). All of these were present in our sample.

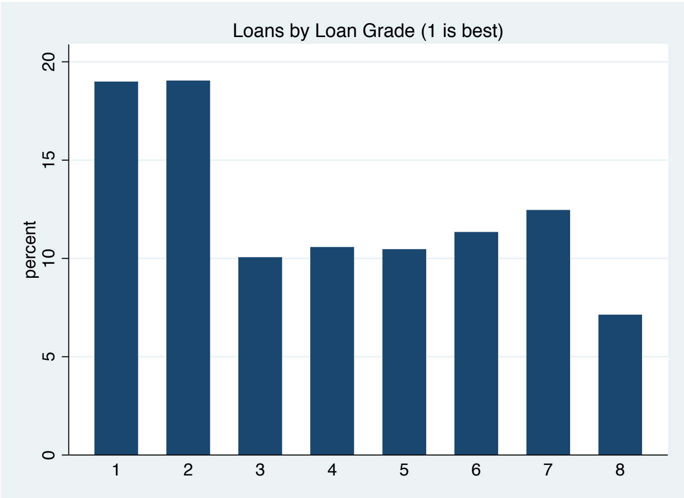
[22] In the words of Newson (2002), we estimate DXY as a performance indicator of X as a predictor of Y.

As a robustness check, we fit a commonly used parametric survival model (i.e., Weibull) using the same covariates and setup (see Appendix). Finally, we run the analysis on a subsample of 20% of our data with similar results.

2.7 Results

Out of 3661 loans on *PeerCo*, 258 defaulted. The average loan amount was € 9014 and loan amounts ranged from € 750 to € 50.000. The average interest rate was 8.8% with a spread from 2.5% to 18%. **Figure 2** denotes the loan distribution by loan grade, ranging from 1 (least risky) to 8 (most risky).

Figure 2 Distribution of Loans by Loan Grade (A-I -> 1-8)



The median age of borrowers of 42 years in our sample is younger than the estimated national average of 47 years[23]. While 72.2% of borrowers in our dataset are male, there is no real difference in default rates based on gender or age based on the descriptive statistics. Regarding occupation, we find that employees account for half of our sample. As expected, civil servants (who often have lifetime contracts in Germany), have a low default rate. Retirees and tradesmen have default rates that are higher than average (for an overview of descriptives see the

[23] https://www.cia.gov/library/publications/the-world-factbook/fields/2177.html

appendix). Results estimated by the Cox model describe the influence of explanatory variables on the probability of a (default) event occurring and on the baseline hazard function. Table 5 below shows the resulting coefficients and standard errors from the Cox regressions of models 1-3, respectively, correcting for time-varying covariates. We follow Moon and Norris (2005), Siering et al. (2016), and Saldanha et al. (2017) for reporting significances.

Model 1 includes hard signals from previous research on lending (Ceyhan et al. 2011), because borrowers with a high *interest rate*, a high *loan amount*, a large *debt-to-income ratio* and a lower *credit grade* are more likely to default. In addition, we add *loan duration* as a control, as our data comprises loans with durations of either 36 or 60 months. Longer loan periods tend to lead to higher default rates. Among the signals in all models, loan duration is not significant (the p-value >.25 led us to drop it from Models 2 and 3), whereas loan amount, number of bids, and interest rate are highly significant in relation to the hazard of default. A higher loan amount or higher interest rate both increase the hazard of default because they make paying back the loan more expensive, reflected in the positive sign of corresponding coefficients. A higher number of bids decrease the hazard of default; thus, less risky projects receive more bids, which seems intuitive as even most novice borrowers are likely to gage the risk-return ratio (e.g. the credit grade and interest rate offered)[24]. For the hard facts, we find that debt-to-income ratio is highly significant across models, while a higher credit grade lowers the risk of default, an effect which is strongest in Model 3. The negative sign for the coefficient for credit grade seems counterintuitive, but is not very significant, marginal in size and can be explained by mixed effects of riskier and less risky loans (i.e., those with an alphabetically lower credit grade) on the hazard. A higher debt-to-income ratio increases the hazard of default as expected.

[24] This could also be explained by social control – perceived pressure to repay loans is likely to increase with the number of bidders.

Table 5 Cox Regressions of Loan Default (Hard Facts, Signals, Soft Facts and other Controls)

	MODEL1		MODEL2		MODEL 3	
VARIABLES	**Coef.**	**S.E.**	**Coef.**	**S.E.**	**Coef.**	**S.E.**
Main Effects:						
Amount	0.0001***	(0.0000)	0.0001***	(0.0000)	0.0001***	(0.0000)
# of bids	-0.0640***	(0.0122)	-0.0575***	(0.0122)	-0.0561***	(0.0124)
Duration	-0.0095	(0.0074)				
# of spatial words[t]			1.2030	(0.9894)	1.4455*	(1.0082)
# of negation words[t]			0.1838**	(0.1098)	0.2012**	(0.1087)
# of modal verbs[t]			-0.2051**	(0.0989)	-0.2146**	(0.0988)
# of modifiers[t]			0.0845***	(0.0360)	0.0903**	(0.0360)
# of positive affect[t]			-0.0625*	(0.0483)	-0.0704*	(0.0478)
# of temporal words[t]			-0.0605**	(0.0364)	-0.0646*	(0.0365)
No greeting[t]			-0.9714***	(0.1735)	-0.9704***	(0.1731)
# of positive emoticons[t]			-1.7723**	(1.0150)	-1.7360**	(1.0177)
Age					-0.0071	(0.0054)
Female					0.1718	(0.1461)
Occupation					0.0802*	(0.0418)
Time-Varying Effects:						
Interest rate	0.0148***	(0.0030)	0.0166***	(0.0030)	0.0167***	(0.0030)
Credit grade	-0.0001	(0.0000)	-0.0001*	(0.0000)	-0.0001**	(0.0000)
Debt-to-income ratio	0.0003***	(0.0001)	0.0002***	(0.0001)	0.0002***	(0.0001)
Model Fit:						
Observations	3,661		3,661		3,661	
AIC	2879		2847		2848	
Somer's D	0.570		0.655		0.653	
Log-Likelihood	-1434		-1410		-1408	

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1, [t] one-tailed

Table 6 Cox Regression of Hard Facts, Signals and Individual Soft Variables

	Model 4		Model 5		Model 6		Model 7		Model 8		Model 9		Model 10	
VARIABLES	**Coef.**	**S.E.**	**Coef.**	**S.E.**	**Coef.**	**S.E.**	**Coef.**	**S.E.**	**Coef.**	**S.E.**	**Coef.**	**S.E.**	**Coef.**	**S.E.**
Main Effects														
Amount	0.0001***	(0.0000)	0.0001***	(0.0000)	0.0001***	(0.0000)	0.0001***	(0.0000)	0.0001***	(0.0000)	0.0001***	(0.0000)	0.0001***	(0.0000)
# of bids	-0.0620***	(0.0123)	-0.0624***	(0.0123)	-0.0680***	(0.0125)	-0.0648***	(0.0123)	-0.0638***	(0.0123)	-0.0647***	(0.0123)	-0.0634***	(0.0122)
Duration	-0.0094	(0.0074)	-0.0094	(0.0074)	-0.0090	(0.0074)	-0.0094	(0.0074)	-0.0094	(0.0074)	-0.0095	(0.0074)	-0.0096	(0.0074)
Word Count	0.0044***	(0.0013)												
Unique Words			0.0065***	(0.0020)										
Pausality					0.0677***	(0.0263)								
# of self-references							0.0473***	(0.0183)						
# of 1st sing. pron.									0.0477**	(0.0198)				
# of 2nd sing. pron.											0.2717***	(0.0865)		
# of typos													0.0580*	(0.0303)
Age														
Female														
Occupation														
Time-Varying Effects														
Interest rate	0.0150***	(0.0030)	0.0150***	(0.0030)	0.0156***	(0.0031)	0.0145***	(0.0030)	0.0144***	(0.0030)	0.0152***	(0.0030)	0.0149***	(0.0030)
Credit grade	-0.0001	(0.0000)	-0.0001	(0.0000)	-0.0001*	(0.0000)	-0.0001	(0.0000)	-0.0001	(0.0000)	-0.0001	(0.0000)	-0.0001	(0.0000)
Debt-to-income ratio	0.0003***	(0.0001)	0.0003***	(0.0001)	0.0003***	(0.0001)	0.0003***	(0.0001)	0.0003***	(0.0001)	0.0003***	(0.0001)	0.0003***	(0.0001)
Model Fit														
Observations	3,661		3,661		3,623		3,661		3,661		3,661		3,661	
AIC	2873		2872		2821		2875		2876		2873		2878	
Somer's D	0.596		0.595		0.575		0.594		0.593		0.582		0.584	
Log-Likelihood	-1429		-1429		-1403		-1431		-1431		-1430		-1432	

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

In Model 2, which adds our linguistic categories to the regression, we find that our proxy variable indicating a missing greeting in a given loan description (i.e., low quality/professionalism) is significant and decreases the hazard as predicted by **H1**. The number of modal verbs (i.e., higher uncertainty) significantly decreases the hazard opposing our hypothesis **H6** while the number of modifiers (i.e., higher expressivity) significantly increases the hazard of default as suggested in **H4**. The number of negation words (one of our measures of uncertainty) is positively and significantly related to hazard of default supporting our hypothesis **H6**, while the number of temporal words (i.e., specificity) is significantly negatively related to the hazard of default, supporting our hypothesis **H7**. The number of positive emotions (an additional measure of positive affect) is significant and negatively related to the hazard of default and moves in the same direction as our other measure of positive affect.

These findings for our linguistic cues extend entirely to Model 3, which implements additional controls for demographic variables age, gender (*female*), and occupation. In Model 3, we find that our control variable lender age slightly decreases the hazard of default, though this is not significant[25]. This effect could be explained by the positive relationship between age and human capital. It may also be related to risk aversion, which is positively related to age. The older people are, the better they may be in realistically assessing their ability to repay loans. It may also be that an older person cares more about the default risk as a stigma than a young person. While the effect of occupation is insignificant overall, we do find some interesting effects per type. For example, being a freelancer lowers the hazard of default. Gender shows no significant effect.

In terms of model fit, likelihood ratio tests reveal that Model 2 has a significantly better fit than Model 1 (Prob > chi2 = 0.0000), while Model 3 has a marginally better fit than Model 2 (Prob

[25] As a curvilinear relationship between age and default risk seemed equally plausible, we also tested the quadratic term for age, which remains insignificant (p=0.254).

> chi2 = 0.0505), indicating that our demographic control variables (in Model 3) do not hold much explanatory power compared with our hard and soft facts (in Models 1 and 2). Similarly, the AIC value drops from 2879 in Model 1 to 2847 in Model 2, also indicating an improvement in fit, while remaining almost the same (AIC = 2848) for Model 3.

Since some of the linguistic cues cannot be measured in our full model (i.e., Model 3) due to reasons such as high correlation with other cues or controls, we measure them separately together with the hard facts in Models 4 to 10 as is common for Cox regressions (Serrano-Cinca et al. 2015). The results of Model 4 suggest that word count (i.e., quantity) is highly significant and positively related to the hazard of default, which contrasts **H1**. For Model 5, the number of unique words (i.e., more diversity) is found to be highly significant and positively related to the hazard of default. This supports **H2a**. A highly significant positive relation of causality in Model 6 was found, which suggests that a higher complexity of texts leads to a higher hazard of default further supporting **H2b**. The Models 7 to 9 are all focused on the linguistic construct immediacy and our highly significant results suggest that there is a positive relation to the hazard of default, opposing our hypothesis **H8**. Finally, the results of Model 10 show some evidence of a higher number of typos leading to a higher hazard of default as suggested in hypothesis **H5**.

Using Somer's D rank correlation, an alternative measure for Cox regressions similar to R^2 in linear regressions, we observe that our Model 1 (i.e., only hard facts and signals) can explain 57% of the variation in the hazard of default. Adding the soft linguistic cues that can be measured within one model improves this explanation to 65.5% for Somer's D in Model 3, reducing the prediction error. The relative improvement of fit by this measure is thereby almost 15%. Additionally, we can see that in the other models that measure the individual linguistic cues (i.e., Models 4-10), the explanatory power also further improves compared with the basic Model 1 with only hard facts. To summarize, the results suggest that the soft linguistic cues do have a rather large impact on explaining hazard of default on the studied p2p lending platform. Below in Table 7 we summarize the hypothesized and actual results.

Table 7 Summary of Hypothesized and Actual Results of Deception Detection Constructs

Hypothesis	Variable	Deceivers should use (hypoth. effect on hazard)	Deceivers here use (effect on hazard)	Supported	Contrary Finding
H1	Quantity	less (-)	more (+)		☑
H2a	Diversity	more (+)	more (+)	☑	
H2b	Complexity	more (+)	more (+)	☑	
H3	Pos. Affect	more (+)	less (-)		☑
H4	Expressivity	more (+)	more (+)	☑	
H5	Quality	more (+)	more (+)	☑	
H6	Uncertainty	more (+)	mixed (+/-)	☑	☑
H7	Specificity	less (-)	less (-)	☑	
H8	Immediacy	less (-)	more (+)		☑

2.8 Discussion of Results

We set out to study deception in IT-mediated P2P lending, particularly the informational value of text for explaining loan default from the backdrop of agency and interpersonal deception theory. Based on our literature review, we focused on the effects of the linguistic constructs diversity, complexity, affect, expressivity, quality, uncertainty, specificity and immediacy on our dependent variable. Keeping this research goal in mind, we discuss our results in light of the literature.

First, contrary to our hypothesis **H1,** we find that a higher quantity of text in loan descriptions raises the hazard of default (Model 4). Thus, defaulting borrowers write more overall (Burgoon et al. 2003; Hancock 2007). Possible explanations for this finding might include liars trying to fabricate a story which already anticipates possible objections that they try to preempt or circumvent by telling a longer story and explaining and justifying themselves. At least three studies support our finding regarding the quantity of words used by borrowers to describe their loan situation and purpose. Ludwig et al. (2016) find that deceivers include more superfluous descriptions in email exchanges. Larrimore et al. (2011) found that lengthier online loan requests on peer-to-peer lending sites were more likely to receive funding, while Flanagin (2007) found that eBay products with longer descriptions received more bids and higher selling prices. Once the talkative (narrative crafting) borrower has his loan he/she might realize that it is not so easy to pay it back (or in the worst case, he/she may have no intention of doing so which would be deceptive if not fraudulent). Overall, our finding for quantity is interesting because people that write more often receive higher rewards; this implies a role for the project size (e.g. coordination and other transaction costs).

Second, as predicted, we find that more *expressive* lenders have a significantly higher hazard of default (**H4**). High-risk borrowers have a strong incentive to color their language in order to convey false low-risk and increase the likelihood of obtaining the desired loan amount. Also, lying is cognitively taxing to most people, which could help explain the effect of expressivity, a sign of cognitive effort or load (Richards 2004).

The empirical results for the measure *complexity* (**H2b**), that more complex language is significantly (positively) related to the hazard of default, in line with our hypothesis, could be explained partially by recent neuroscientific studies: fMRI studies have shown that the prefrontal cortex – the brain region involved in executive control – is more heavily active when lying, a cognitively taxing task (Langleben et al. 2005). One reason for this could be that we are habitualized from a young age to tell the truth which therefore comes more naturally and should require less effort. Thus, we might expect to find language artifacts related to (heavy) cognition. Intuitively, signs of such conscious effort could be high variation in vocabulary use (e.g., the use of unique words), *expressivity,* and *complexity* (as measured by the increased use of punctuation).

As expected, higher language diversity in loan applications is positively related to the hazard of default, in line with hypothesis (**H2a**). The findings are robust towards the inclusion of additional control variables and the use of different statistical models.[26] The evidence supports the hypothesized motive of persuasion as indicated by expressivity, which is in line with Zhou et al. (2004b, 2008) and Newman (2003). Liars often do not access real memory, but rather fabricate information, a cognitively taxing process (Hancock et al. 2004; Zhou et al. 2004a). An alternative explanation could also help explain this result in the setting of P2P lending: the number of unique words used (i.e., diversity) suggests a higher variety in vocabulary of an individual, which can be a sign of a higher level of education. Education is a predictor of income, which one would expect to be positively related to repayment ability. While our data does not explicitly provide data on educational background, our descriptive statistics and robustness tests suggest that additional age somewhat raises the hazard of default, though this difference is not significant, even when a quadratic term for age is formed.

Next, we find that a higher number of typographical errors, our main measure of quality/professionalism, is significantly related to the hazard of default, in line with our hypothesis (**H5**), which could be a sign of such cognitive overload but also in line with our results for complexity (**H2b**), as the complexity of an issue increases the chances of making mistakes.

[26] As a robustness check, we had a look at each of the soft variables of our data using another type of survival analysis: Weibull regression. Our findings remain stable, though model fit is not as good as with the more robust and conservative Cox model, see Table 16 of the Appendix.
Further, to rule out that our results are simply random significance due to the sample size, we ran a regression on a subsample (with a comparable percentage of defaulting loans) with similar results.

We also find that 'no (initial) greeting' at the beginning of loan description texts is related to a significantly lower hazard of default. Intuitively, borrowers who omit an informal greeting could be more serious in their language, hinting at more serious behavior. The presence of such greeting phrases might also indicate purposefully overconstructed text (e.g. brownnosing). Our findings for informal greetings (which we interpret as a quality indicator) relate to studies of textual conversations on Reddit, which suggest a role for politeness in increasing the probability of receiving an answer to a Q&A request but find no such effect (Althoff et al. 2014). Uttering a greeting can also be interpreted as a speech act (Ludwig et al. 2016; Mohr 2007). Next, while we find that potential deceivers show significant *specificity* patterns in their language use (**H7**), our finding for this construct is mixed: While increased spatial specificity (i.e., location-related information) is positively but not significantly related to the hazard of loan default, contrary to our expectation, temporal specificity (i.e., providing more time-related information) in language exhibits the opposite effect, in line with our hypothesis. By providing more specific information, deceitful borrowers may hope to avoid outing themselves by giving too little information; more precisely, they might try to fabricate a convincing story, enhanced by specifics (Hancock et al. 2007; Newman et al. 2003).

We also find that our measure of *uncertainty* (i.e. increased use of modal verbs indicating ambiguity) leads to a lower hazard of default, counter to our corresponding hypothesis (**H7**). However, our second measure of uncertainty, negation words, leads to a higher hazard, creating a mixed picture here. While only four of the empirical studies identified in Table 2 report results on uncertainty in language, the authors find that liars in their studies use more uncertain words. An explanation for our contrary finding for this construct could be that liars would not want to seem uncertain in the context of P2P lending, because this might seem less creditworthy (Qin et al. 2005). Also it is conceivable that high-risk borrowers might want to make explicit (e.g., certain) promises to seem more creditworthy. The asynchronous nature of P2P lending communication allows the editing of written texts and might therefore support this.

Further, positive affect (**H3**) and immediacy (**H8**) exhibit significant effects that run counter to our hypotheses. While some studies find that liars use more affect words, it has also been found that emotions draw attention (Gigerenzer and Selten 2001), which is usually what deceivers want to avoid, possibly explaining our result for H3, that the usage of positive affect in loan descriptions is correlated with a significantly lower hazard of default. Most recent deception studies in fact find that liars *disassociate* themselves from their lies due to the psychological cost of lying and lower verifiability (Hancock et al. 2007; Qin et al. 2005; Toma and Hancock 2010; Zhou et al. 2004a; Zhou and Zhang 2008).

Therefore, we expected that high-risk borrowers – given that they are assumed to exhibit deceptive intent – would use fewer *self-references,* i.e., be less *immediate* (**H8**). However, our findings for this variable are significant in the opposite direction – a higher usage of self-references is significantly related to a higher hazard of default. We come up with a theory-based and a setup-based explanation for this deviation.

First, when a borrower explains his reasons for requiring a loan, he might appear most trustworthy if he refers to himself and his miserable situation. Literature revealed that borrowers can improve credit conditions if they shape their identity as being in an "*economic hardship"* (Herzenstein et al. 2011). Hence, packaging of explanations in a 'need' frame can greatly influence perceptions of trustworthiness (Elsbach and Elofson 2000). Therefore, if a deceptive lemon's intention to persuade and create familiarity (over)compensates for the intention to disassociate from the deception, we might expect the number of self-references to increase sufficiently to counter the expected effect on immediacy for **H8**.

Second, previous findings may also be an artifact of an obtrusive setup of the experiments conducted in which constructs were developed. In most such experiments, selected participants were given the task of consciously lying about certain facts before measuring their language use (e.g., Burgoon et al. 2003; Hancock et al. 2007; Marett and George 2004; Newman et al. 2003; Qin et al. 2005; Toma and Hancock 2010; Zhou et al. 2004b). Potentially, by increasing the psychological costs of deception, the (perceived) need to lie is what triggers the intent to disassociate oneself from it in the first place. Hence, if a person the makes the decision to deceive the motive to disassociate might be less relevant than the incentive to be persuasive. In the setting of our p2p lending platform, the borrower signaling behavior we observe in project description texts may well be a weaker form of deception - window dressing (or impression management) - rather than lying in the classical sense.

We reasoned in our theory section that liars' lack of knowledge of the issue could lead to lower complexity in language use (Zhou et al. 2004a), but that the opposite effect suggested by neuroscience seemed more convincing. Upon careful reflection (of H2b), it seems that knowledge of one's true creditworthiness does not seem to be a precondition to coloring or even fabricating loan descriptions.

2.9 Implications for Theory and Practice

These findings have theoretical and practical consequences for IS and management research since signaling and screening processes in P2P lending are evidently not yet far enough evolved to minimize transaction costs (e.g., search and information costs and the costs of policing and monitoring). Our evidence demonstrates that the inefficiency of a self-regulated P2P lending market still requires intermediaries to reduce these transaction costs (Bhattacharya and Thakor 1993; Stigler 1961; Williamson 1981). Our findings cast doubt on the electronic marketplace hypothesis, which maintains that the increasing role of electronic lending marketplaces leads to disintermediation by replacing banks and insurance companies (Hulme and Wright 2006). Just as Bailey and Bakos predict (1997), the roles of these intermediaries must be different. They do not need to execute the screening process themselves, like banks, but they do need to prepare and verify information since borrowers seem unable to decide correctly how information should be evaluated and weighed (Perry 2008).

We contribute to the literature on the management of information systems in several ways. Our study is among the early larger studies of the informational value of texts in P2P lending and also addresses the fundamental issue of asymmetric information. We contribute to the growing literature on textual analysis by examining linguistic features that have been identified as pertaining to deception on a peer-to-peer platform. In addition, we contribute to specialized research streams in computer linguistics, social psychology and economic psychology, by providing baseline data on deception detection in P2P lending and by suggesting fruitful avenues for further interdisciplinary studies, such as the differentiation between deception of others and self-deception.

Furthermore, we add to the discussion on intermediaries in financial transactions (Bailey and Bakos 1997; Datta and Chatterjee 2008) by observing that hard facts alone do not explain the variation in true risk and that lenders make inefficient decisions. We therefore confirm a recent finding of Mild et al. (2015) that lenders can fail to transform available information into the right decisions, i.e., by failing to set the correct interest rate (Mild et al. 2015). With a Somer's D rank correlation of .655 (compared with .570), we find that incorporating soft information reduces the prediction error regarding the hazard of P2P financing related loan default (increasing explanatory power), lending support to our assertion that (some) lemons attempt to deceive (themselves or others). Further, we contribute to the literature stream on decision support using big data analysis for credit decisions by providing evidence of deception detection cues that feed into improved detection algorithms, enabling design science approaches. Finally, by clarifying which parts of IDT apply most clearly to asynchronous communication (in Table 15), we contribute to methodology that uses the theory in this setting.[27]

This study also has several practical implications for improving credit risk scoring and fraud detection. First, for platforms looking to reduce the number of fraudulent or misleading statements, this study provides insights into the extent of deception in P2P lending. Managing the risks of default is a crucial challenge for the crowdlending industry, which largely focuses on higher risk loans. Such platforms should provide more verifiable information to increase the value and credibility of borrower signals. Additionally, the information must be presented in a more intuitive way to be comprehensible to inexperienced lenders. To remain competitive in a bustling market, this is a pivotal service provided to investors/lenders by the intermediary. Alternatively, the *interest rate* could be set professionally by the platform, as successfully executed by the successful American P2P lending platform *LendingClub* (Lending Club 2011). Our findings can also feed into algorithms designed to detect lemons in computer-mediated communication (CMC). This is applicable to the web-enabled decision support systems of banks or P2P lending platforms particularly when extended to other social profiles on the web such as in the case of large-scale credit risk scoring.[28] Further, the methods highlighted could facilitate future research on platform design (Casenove and Miraglia 2014; Sage 1981), e.g. the impact of extending evaluation tools for potential investors on the platforms (e.g., through traffic light systems that include soft information) which increasingly also extend to mobile applications. Our findings also shed light on borrower ethics, as some seem to be committing loan description fraud in response to economic incentives and lacking sanctioning mechanisms

[27] See Table 15 in the appendix

[28] Platforms like ZestFinance and Think Finance use a combination of machine learning and large-scale big data analysis for improved credit scoring and underwriting. For a detailed report on this emerging software market see page 7 of this report: http://www.morganstanley.com/sustainableinvesting/pdf/Big_Data_Big_Potential.pdf

and are thereby reducing loan availability for fully truthful lenders. Platforms could rule out unethical behavior and highlight the legal consequences of fraud in their terms and conditions.

Since voluntary control by P2P lenders is not sufficient, independent outside bodies should not only better educate small lenders about the risks and rewards of crowdlending, but also routinely audit small, random samples of loans. The resulting information would also benefit tax authorities and consumer protection agencies. A first step to improving such education was taken in Germany with the Retail Investor Protection Act, passed into law in 2015 that requires lending platforms to publicly provide a prospectus. To give the corresponding agencies or bodies the necessary authority for such controls, regulations on crowdlending (such as the Jobs Act in the US) could be amended. Such legislation should be strict enough to reduce fraud, but loose enough to allow for innovation and growth. It is worth noting here that P2P lending interest rates, while relatively high, are still lower than those provided by heavily criticized payday loan vendors. Therefore, by democratizing (and professionalizing) micro lending, P2P lenders may have positive social impacts by decreasing the size of the black market for lending and bringing more loans into the tax system. Further, P2P platforms also have the potential to reduce discrimination in lending.

2.10 Limitations and Future Research

In this paper, we restrict our analysis to a single crowdlending platform. Further, more work is needed on motivation of crowdlenders: We implicitly assume that high-risk borrowers behave rationally and therefore potentially have some degree of deceptive intent. We do not assume that all high-risk borrowers lie or in our context deceive lenders about their creditworthiness; rather, our model implicitly assumes that deception occurs more frequently among those with high default rates and that this deception is reflected in the measurement items as suggested by theory. It is conceivable that some borrowers lack knowledge about their own high-risk and therefore borrow overconfidently (Hirshleifer 2001) and not because of deceptive intent. Overconfidence could be interpreted as a form of self-deception. However, we believe that our assumption has little effect on our results for two reasons: First, it is feasible that some borrowers who deceive on their loan applications just to obtain the loan may nonetheless intend to pay it back; in such a case, deception in the loan descriptions would remain. Further, Fischbacher and Föllmi-Heusi (2013) demonstrate that deceptive behavior in a dice roll experiment can be inferred from the underlying outcome distribution. This implies that even if only a portion of defaults follow borrowers' deceptive behavior, the effect should still be potent overall, given the strong incentive to provide misleading information.

A limitation of our dataset is that we cannot control for past borrowing behavior because most of the loans in our dataset are first-time P2P loans. First-time borrowers may exhibit less professionalism in their loan descriptions, but those that misrepresent their creditworthiness are unlikely to have adapted their strategies, which may improve the rate of deception detection when compared with experienced borrowers.[29] Further, the average word count for loan descriptions in our study is not very high but at about the value suggested by the authors of LIWC software for high accuracy.[30] A further limitation is nonetheless given by the imperfect analysis algorithm of LIWC.

The accuracy of LIWC of 68% appears to be significantly higher than that of human lie detectors (Newman et al. 2003). This still implies that deception is not detected in 32% of cases. Therefore, both false positives and false negatives are possible. This implies the need for more replication studies with additional dictionaries. Such misclassification affects our interpretation of analyzed loan descriptions in two important ways. First, the actual rate of deception in loan

[29] Proposition 9 of IDT states that: „Skilled deceivers appear more believable because they make more strategic moves and display less leakage than unskilled deceivers" (Griffin 2006).
[30] We originally included both the loan titles and the description, which would increase word count by over 10%, but decided to remove the titles because these can be repeated in descriptions, which might have otherwise abnormally amplified the occurrence of certain words.

descriptions on *PeerCo* could potentially be higher or lower than detected. Second, the existence of false positives implies that perfectly honest borrowers may sometimes use words (unigrams) or sentence structures that raise suspicion of deception. However, studies suggest that LIWC results in many fewer false positives than human judgment (Ziegler et al. 2011, p. 318).

Also, we can expect mixed results. For instance, significant results are obstructed if enough borrowers use the constructs but do not default (e.g. due to their general expressiveness or due to luck), or in case some overconfident borrowers do not use the constructs (e.g. they could be so confident that they think they do not need to persuade others in textual form). Mixed support and some contrary findings seem to support the latter explanation. However, what we demonstrate is that lemons (e.g., high-risk borrowers) in online P2P lending write loan descriptions which are significantly different in style than those of low-risk borrowers. We can assume that they are consciously or subconsciously aware of their high risks and express this knowledge in a particular language style.

Future work could extend our findings to other platforms. This may help disentangle detection of phenomena from their corresponding industry context (e.g., online dating vs. P2P lending). It might also be interesting to look at historical borrowing activities by platform members as more loan data becomes available. Also, the role of self-deception in loan applications could be further explored. Self-deception occurs when someone maintains a false belief in light of information that could lead to forming the correct belief (Trivers 2014). In the context of P2P lending platforms, it is conceivable that borrowers may become overconfident in order to persuade others more effectively. Also, the link between latency, e.g. the time it takes to a user to post a textual description and deception, could be further explored (Benjamin et al. 2016; Ho et al. 2016), perhaps by integrating eye-tracking technology (Proudfoot et al. 2016). Lastly, for IS practitioners, we reason that the role of intermediary (traditionally performed by banks) could be executed through the P2P lending platform itself, independent third parties, or through borrower groups (Ashta and Assadi 2010; Berger and Gleisner 2009; Chircu and Kauffman 2000). The creation of borrower pools that share the risk of each other's debt is probably the cheapest option, but also the least acknowledged. This type of contract could be greatly facilitated by the recent emergence of the blockchain (and cryptocurrencies), which make ultra low-cost transactions feasible. Incorporating the blockchain (and its global transaction ledger) into P2P lending would also facilitate information verification, which is likely to reduce transaction costs for all parties involved.[31]

2.11 Summary and Concluding Remarks

Our research enlivens debate on the use of linguistic cues to improve automated analysis of soft information in crowdlending. We evaluate the research question 'Can linguistic cues in soft information of IT-mediated P2P lending project descriptions help explain loan default?' on the basis of agency and interpersonal deception theory. We find linguistic deception cues, specifically the measures of *quantity, expressivity*, *complexity*, *specificity* and *diversity,* to be significant predictors for risk above and beyond hard facts. Our study blends research on interpersonal deception and asymmetric information in a computer-mediated context with the evaluation of lending outcomes. Further, unlike many previous studies which ask subjects to lie before testing for linguistic deception cues, our approach avoids the risk of influencing borrower behavior. Without efficient monitoring and control, information quality on crowd-based platforms can be undermined and exploited by individuals. Our work underscores the need for more studies using content analysis and specifically, novel detection and prediction models that can play important roles in both predictive analytics and in the design of screening mechanisms. The high interest rates on P2P lending platforms reflect the lower cost structure

[31] The first such platforms are now emerging, e.g. celsius.network and lendoit.com

of semi-automating the lending process online and the focus on previously underserved niche markets, but also the underlying systemic risk for lenders which is in need of further study.

2.12 References (First empirical study)

Akaike, H. 1974. "A New Look at the Statistical Model Identification," *IEEE Transactions on Automatic Control* (19:6), pp. 716–723.

Akerlof, G. A. 1970. "The Market for 'Lemons': Quality Uncertainty and the Market Mechanism," *The Quarterly Journal of Economics* (84:3), pp. 488–500.

Allison, P. D. 2014. *Event History and Survival Analysis*, Los Angeles: SAGE Publications.

Allison, T. H., Davis, B. C., Short, J. C., and Webb, J. W. 2015. "Crowdfunding in a Prosocial Microlending Environment: Examining the Role of Intrinsic Versus Extrinsic Cues," *Entrepreneurship Theory and Practice* (39:1), pp. 53–73.

Althoff, T., Danescu-Niculescu-Mizil, C., and Jurafsky, D. 2014. "How to Ask for a Favor: A Case Study on the Success of Altruistic Requests," in *ICWSM 2014 Proceedings*.

Ashta, A., and Assadi, D. 2010. "The Use of Web 2.0 Technologies in Online Lending and Impact on Different Components of Interest Rates," in *Advanced Technologies for Microfinance: Solutions and Challenges*, France: Groupe ESC Dijon Bourgogne, pp. 206–224.

Bailey, J. P., and Bakos, Y. 1997. "An exploratory study of the emerging role of electronic intermediaries," *International Journal of Electronic Commerce* (1:3), pp. 7–20.

Barley, S. R., Meyer, G. W., and Gash, D. C. 1988. "Cultures of culture: Academics, practitioners and the pragmatics of normative control," *Administrative Science Quarterly*, pp. 24–60.

Baum, C. F. 2006. *An introduction to modern econometrics using Stata*, 1. ed., College Station, USA: Stata Press.

Benjamin, V., Zhang, B., Nunamaker, J. F., and Chen, H. 2016. "Examining Hacker Participation Length in Cybercriminal Internet-Relay-Chat Communities," *Journal of Management Information Systems* (33:2), pp. 482–510.

Benyus, J., Bremmer, I., Pujadas, J., Christakis, N., Collier, P., Warnholz, J., et al. 2009. "Breakthrough ideas for 2009," *Harvard Business Review* (87:2), pp. 19–40.

Berelson, B. 1952. *Content analysis in communication research.*, 1. ed., Michigan, USA: University of Michigan.

Berger, S. C., and Gleisner, F. 2009. "Emergence of financial intermediaries in electronic markets: The case of online P2P lending," *Business Research* (2:1), pp. 39–65.

Bhattacharya, S., and Thakor, A. V. 1993. "Contemporary banking theory," *Journal of Financial Intermediation* (3:1), pp. 2–50.

Bloomberg 2016. *LendingClub Models Misfire as Loan Write-Offs Top Forecasts*. In *Bloomberg.com*, retrieved 11. February, 2016, from http://www.bloomberg.com/news/articles/2016-02-05/lendingclub-models-misfire-as-loan-write-offs-exceed-forecasts.

Box-Steffensmeier, J. M., and Zorn, C. J. W. 2001. "Duration Models and Proportional Hazards in Political Science," *American Journal of Political Science* (45:4), pp. 972–988.

Bretschneider, U., and Leimeister, J. M. 2017. "Not just an ego-trip: Exploring backers' motivation for funding in incentive-based crowdfunding," *The Journal of Strategic Information Systems*.

Breusch, T. S., and Pagan, A. R. 1979. "A Simple Test for Heteroscedasticity and Random Coefficient Variation," *Econometrica* (47:5), pp. 1287–1294.

Briscoe, E. J., Appling, D. S., and Hayes, H. 2014. "Cues to deception in social media communications," in *System Sciences (HICSS), 2014 47th Hawaii International Conference on*, IEEE, pp. 1435–1443.

Brüderl, J., Preisendörfer, P., and Ziegler, R. 1992. "Survival Chances of Newly Founded Business Organizations," *American Sociological Review* (57:2), pp. 227–242.

Buller, D. B., and Burgoon, J. K. 1996. "Interpersonal deception theory," *Communication Theory* (6:3), pp. 203–242.

Burgoon, J. K., Blair, J., Qin, T., and Nunamaker Jr, J. F. 2003. "Detecting deception through linguistic analysis," in *Intelligence and Security Informatics*, H. Chen, R. Miranda, D. Zeng, C. Demchak, J. Schroeder and T. Madhusudan (eds.), Berlin, Heidelberg: Springer, pp. 91–101.

Burgoon, J. K., Buller, D. B., Guerrero, L. K., Afifi, W. A., and Feldman, C. M. 1996. "Interpersonal deception: Information management dimensions underlying deceptive and truthful messages," *Communications Monographs* (63:1), pp. 50–69.

Burns, M. B., and Moffitt, K. C. 2014. "Automated deception detection of 911 call transcripts," *Security Informatics* (3:1), pp. 1–9.

Burtch, G., Ghose, A., and Wattal, S. 2014. "Cultural Differences and Geography as Determinants of Online Prosocial Lending," *MIS Quarterly* (38:3), pp. 773–794.

Burtch, G., Hong, Y., and Liu, D. 2018. "The Role of Provision Points in Online Crowdfunding," *Journal of Management Information Systems* (35:1), pp. 117–144.

Campbell, T. S., and Kracaw, W. A. 1980. "Information Production, Market Signalling, and the Theory of Financial Intermediation," *Journal of Finance* (35:4), pp. 863–882.

Carlson, J. R., George, J. F., Burgoon, J. K., Adkins, M., and White, C. H. 2004. "Deception in computer-mediated communication," *Group Decision and Negotiation* (13:1), pp. 5–28.

Casenove, M., and Miraglia, A. 2014. "Botnet over Tor: The illusion of hiding," in *2014 6th International Conference On Cyber Conflict (CyCon 2014)*, pp. 273–282.

Caspi, A., and Gorsky, P. 2006. "Online deception: Prevalence, motivation, and emotion," *CyberPsychology & Behavior* (9:1), pp. 54–59.

Ceyhan, S., Shi, X., and Leskovec, J. 2011. "Dynamics of Bidding in a P2P Lending Service: Effects of Herding and Predicting Loan Success," in *Proceedings of the 20th International Conference on World Wide Web*, New York: ACM, pp. 547–556.

Chircu, A. M., and Kauffman, R. J. 2000. "Reintermediation strategies in business-to-business electronic commerce," *International Journal of Electronic Commerce* (4:4), pp. 7–42.

Cleves, M., Gould, P. W., Gutierrez, R. G., and Marchenko, Y. V. 2010. *An Introduction to Survival Analysis Using Stata*, 3. ed., College Station: Stata Press.

Cook, T. D., and Campbell, D. T. 1979. *Quasi-experimentation: Design & analysis issues for field settings*, Boston, USA: Rand McNally College.

Cox, D. R. 1972. "Regression Models and Life-Tables," *Journal of the Royal Statistical Society. Series B (Methodological)* (34:2), pp. 187–220.

Cox, D. R. 1975. "Partial likelihood," *Biometrika* (62:2), pp. 269–276.

Crawford, V. P., and Sobel, J. 1982. "Strategic information transmission," *Econometrica* (50:6), pp. 1431–1451.

Daft, R. L., and Lengel, R. H. 1986. "Organizational information requirements, media richness and structural design," *Management Science* (32:5), pp. 554–571.

Datta, P., and Chatterjee, S. 2008. "The economics and psychology of consumer trust in intermediaries in electronic markets: The EM trust framework," *European Journal of Information Systems* (17:1), pp. 12–28.

DePaulo, B. M., Lindsay, J. J., Malone, B. E., Muhlenbruck, L., Charlton, K., and Cooper, H. 2003. "Cues to deception," *Psychological Bulletin* (129:1), p. 74.

Dibbern, J., Goles, T., Hirschheim, R., and Jayatilaka, B. 2004. "Information Systems Outsourcing: A Survey and Analysis of the Literature," *ACM SIGMIS Database* (35:4), pp. 6–102.

Drogalas, G., Pazarskis, M., Anagnostopoulou, E., and Papachristou, A. 2017. "The effect of internal audit effectiveness, auditor responsibility and training in fraud detection," *Journal of Accounting and Management Information Systems* (16:4), pp. 434–454.

Efron, B. 1977. "The Efficiency of Cox's Likelihood Function for Censored Data," *Journal of the American Statistical Association* (72:359), pp. 557–565.

Elsbach, K. D., and Elofson, G. 2000. "How the packaging of decision explanations affects perceptions of trustworthiness," *Academy of Management Journal* (43:1), pp. 80–89.

Emekter, R., Tu, Y., Jirasakuldech, B., and Lu, M. 2015. "Evaluating Credit Risk and Loan Performance in Online Peer-to-Peer (p2p) Lending," *Applied Economics* (47:1), pp. 54–70.

Farrell, J., and Rabin, M. 1996. "Cheap talk," *The Journal of Economic Perspectives* (10:3), pp. 103–118.

Feller, J., Gleasure, R., and Treacy, S. 2017. "Information sharing and user behavior in internet-enabled peer-to-peer lending systems: an empirical study," *Journal of Information Technology* (32:2), pp. 127–146.

Fischbacher, U., and Föllmi-Heusi, F. 2013. "Lies in Disguise-an Experimental Study on Cheating," *Journal of the European Economic Association* (11:3), pp. 525–547.

Flanagin, A. J. 2007. "Commercial Markets as Communication Markets: Uncertainty Reduction Through Mediated Information Exchange in Online Auctions," *New Media & Society* (9:3), pp. 401–423.

Gao, Q., Lin, M., and Sias, R. W. 2017. *Words Matter: The Role of Texts in Online Credit Markets*, Rochester, NY: Social Science Research Network.

Gefen, D., and Rigdon, E. E. 2011. "An update and extension to SEM guidelines for administrative and social science research," *MIS Quarterly* (35:2), pp. iii-A7.

Gefen, D., Straub, D. W., and Boudreau, M. C. 2000. "Structural equation modeling and regression: Guidelines for research practice," *Communications of the Association for Information Systems* (4:7), pp. 1–70.

Gigerenzer, G., and Selten, R. 2001. "The adaptive toolbox," *Bounded rationality: The adaptive toolbox*, pp. 37–50.

Gonzalez, L., and Loureiro, Y. K. 2014. "When can a photo increase credit? The impact of lender and borrower profiles on online peer-to-peer loans," *Journal of Behavioral and Experimental Finance* (2), pp. 44–58.

Grambsch, P. M., and Therneau, T. M. 1994. "Proportional Hazards Tests and Diagnostics Based on Weighted Residuals," *Biometrika* (81:3), pp. 515–526.

Greiner, M. E., and Wang, H. 2010. "Building consumer-to-consumer trust in e-finance marketplaces: An empirical analysis," *International Journal of Electronic Commerce* (15:2), pp. 105–136.

Griffin, E. 2006. *Communication: A First Look at Communication Theory*, New York: McGraw-Hill.

Hancock, J. T. 2007. "Digital Deception: Why, When and How People Lie Online," in *Oxford Handbook of Internet Psychology*, A. Joinson, K. McKenna, T. Postmes and U.-D. Reips (eds.), Oxford: Oxford University Press, pp. 289–301.

Hancock, J. T., Curry, L. E., Goorha, S., and Woodworth, M. 2007. "On lying and being lied to: A linguistic analysis of deception in computer-mediated communication," *Discourse Processes* (45:1), pp. 1–23.

Hancock, J. T., Curry, L., Goorha, S., and Woodworth, M. T. 2004. "Lies in Conversation: An Examination of Deception Using Automated Linguistic Analysis," in *Proceedings of the Annual Conference of the Cognitive Science Society*, pp. 534–540.

Herzenstein, M., Andrews, R. L., Dholakia, U., and Lyandres, E. 2008. "The democratization of personal consumer loans? Determinants of success in online peer-to-peer lending communities," *Boston University School of Management Research Paper*.

Herzenstein, M., Sonenshein, S., and Dholakia, U. M. 2011. "Tell me a good story and I may lend you money: The role of narratives in peer-to-peer lending decisions," *Journal of Marketing Research* (48:Special Issue), pp. 138–149.

Hildebrand, T., Puri, M., and Rocholl, J. 2017. "Adverse Incentives in Crowdfunding," *Management Science* (63:3), pp. 587–608.

Hirshleifer, D. 2001. "Investor psychology and asset pricing," *The Journal of Finance* (56:4), pp. 1533–1597.

Ho, S. M., Hancock, J. T., Booth, C., and Liu, X. 2016. "Computer-Mediated Deception: Strategies Revealed by Language-Action Cues in Spontaneous Communication," *Journal of Management Information Systems* (33:2), pp. 393–420.

Ho, S. M., Hancock, J. T., Booth, C., Liu, X., Timmarajus, S. S., and Burmester, M. 2015. "Liar, Liar, IM on Fire: Deceptive language-action cues in spontaneous online communication," in *Intelligence and Security Informatics (ISI), 2015 IEEE International Conference on*, IEEE, pp. 157–159.

Hoegen, A., Steininger, D. M., and Veit, D. 2017. "How do Investors Decide? An Interdisciplinary Review of Decision-Making in Crowdfunding," *Electronic Markets*, p. forthcoming.

Hogue, J. 2015. *Crowdfunding 2015: Growth, Platform Failures and IPOs*. In *Crowd 101*, retrieved 2. October, 2017, from https://www.crowd101.com/crowdfunding-2015-growth-platform-failures-ipos/.

Homburg, C., and Giering, A. 1998. "Konzeptualisierung und Operationalisierung komplexer Konstrukte: Ein Leitfaden für die Marketingforschung," in *Die Kausalanalyse*, Stuttgart, Germany: Schäffer-Poeschel, pp. 111–146.

Horne, D. R., Norberg, P. A., and Ekin, A. C. 2007. "Exploring consumer lying in information-based exchanges.," *Journal of Consumer Marketing* (24:2), pp. 90–99.

Hulme, M. K., and Wright, C. 2006. "Internet based social lending: Past, present and future," *Social Futures Observatory* (115).

Hurkens, S., and Kartik, N. 2009. "Would I lie to you? On social preferences and lying aversion," *Experimental Economics* (12:2), pp. 180–192.

Insch, G. S., Moore, J. E., and Murphy, L. D. 1997. "Content Analysis in Leader ship Research: Examples, Procedures, and Suggestions for Future Use," *Leadership Quarterly* (8:1), pp. 1–25.

Iyer, R., Khwaja, A. I., Luttmer, E. F. P., and Shue, K. 2009. *Screening in New Credit Markets: Can Individual Lenders Infer Borrower Creditworthiness in Peer-to-Peer Lending?*

Iyer, R., Khwaja, A. I., Luttmer, E. F. P., and Shue, K. 2015. "Screening Peers Softly: Inferring the Quality of Small Borrowers," *Management Science* (Articles in Advance), pp. 1–24.

Joinson, A. N., and Dietz-Uhler, B. 2002. "Explanations for the perpetration of and reactions to deception in a virtual community," *Social Science Computer Review* (20:3), p. 275.

Jones, T. M. 1991. "Ethical decision making by individuals in organizations: An issue-contingent model," *Academy of Management Review* (15:2), pp. 366–395.

Kennedy, P. 2008. *A Guide to Econometrics*, 6. ed., Malden: Wiley-Blackwell.

Kim, K., and Viswanathan, S. 2014. "The Experts in the Crowd: The Role of Reputable Investors in a Crowdfunding Market," *SSRN*.

Knapp, M. L., and Comadena, M. E. 1979. "Telling it like it isn't: A review of theory and research on deceptive communications," *Human Communication Research* (5:3), pp. 270–285.

Knowledge@Wharton 2017. *Peer-to-Peer Lending: Ready to Grow, Despite a Few Red Flags*. In *Knowledge@Wharton*, retrieved 11. February, 2017, from http://knowledge.wharton.upenn.edu/article/peer-peer-lending-ready-grow-despite-red-flags/.

Kutner, M. H., Nachtsheim, C., and Neter, J. 2004. *Applied linear regression models*, 4. ed., OH, USA: McGraw-Hill/Irwin.

Langleben, D. D., Loughead, J. W., Bilker, W. B., Ruparel, K., Childress, A. R., Busch, S. I., et al. 2005. "Telling truth from lie in individual subjects with fast event-related fMRI," *Human brain mapping* (26:4), pp. 262–272.

Larrimore, L., Jiang, L., Larrimore, J., Markowitz, D., and Gorski, S. 2011. "Peer to peer lending: The relationship between language features, trustworthiness, and persuasion success," *Journal of Applied Communication Research* (39:1), pp. 19–37.

Lee, E., and Lee, B. 2012. "Herding behavior in online P2P lending: An empirical investigation," *Electronic Commerce Research and Applications* (11:5), pp. 495–503.

Leland, H. E., and Pyle, D. H. 1977. "Informational asymmetries, financial structure, and financial intermediation," *Journal of finance*, pp. 371–387.

Lending Club 2011. *Statistics Lending Club*. In retrieved 28. November, 2011, from http://www.lendingclub.com/.

Li, Y., Rakesh, V., and Reddy, C. K. 2016. "Project Success Prediction in Crowdfunding Environments," in *Proceedings of the Ninth ACM International Conference on Web Search and Data Mining*, New York, NY, USA: ACM, pp. 247–256.

Lin, M., Prabhala, N. R., and Viswanathan, S. 2013. "Judging Borrowers by the Company They Keep: Friendship Networks and Information Asymmetry in Online Peer-to-Peer Lending," *Management Science* (59:1), pp. 17–35.

Lodh, S. C., and Gaffikin, M. J. R. 1997. “Critical Studies in Accounting Research, Rationality and Habermas: A Methodological Reflection,” *Critical Perspectives on Accounting* (8:5), pp. 433–474.

Logsdon, J. M., and Patterson, K. D. W. 2010. “Deception in business networks: Is it easier to lie online?,” *Journal of Business Ethics* (90:Suppl 4), pp. 537–549.

Luca, M., and Zervas, G. 2013. *Fake It Till You Make It: Reputation, Competition, and Yelp Review Fraud*.

Ludwig, S., van Laer, T., de Ruyter, K., and Friedman, M. 2016. “Untangling a Web of Lies: Exploring Automated Detection of Deception in Computer-Mediated Communication,” *Journal of Management Information Systems* (33:2), pp. 511–541.

Marett, L. K., and George, J. F. 2004. “Deception in the case of one sender and multiple receivers,” *Group Decision and Negotiation* (13:1), pp. 29–44.

Massolution 2013. *2013 CF Industry Report*.

Maxwell, S. E. 2000. “Sample size and multiple regression analysis,” *Psychological Methods* (5:4), pp. 434–458.

Mayzlin, D., Dover, Y., and Chevalier, J. 2014. “Promotional Reviews: An Empirical Investigation of Online Review Manipulation,” *American Economic Review* (104:8), pp. 2421–2455.

McMahon, J. M., and Harvey, R. J. 2006. “An analysis of the factor structure of Jones’ moral intensity construct,” *Journal of Business Ethics* (64:4), pp. 381–404.

Michels, J. 2012. “Do Unverifiable Disclosures Matter? Evidence from Peer-to-Peer Lending,” *Accounting Review* (87:4), pp. 1385–1413.

Mild, A., Waitz, M., and Wöckl, J. 2015. “How low can you go? — Overcoming the inability of lenders to set proper interest rates on unsecured peer-to-peer lending markets,” *Journal of Business Research* (68:6), pp. 1291–1305.

Milgrom, P., and Roberts, J. 1992. *Economics, organization and management*.

Miller, S. 2015. “Information and default in consumer credit markets: Evidence from a natural experiment,” *Journal of Financial Intermediation* (24:1), pp. 45–70.

Mitra, T., and Gilbert, E. 2014. “The Language That Gets People to Give: Phrases That Predict Success on Kickstarter,” in *Proceedings of the 17th ACM Conference on Computer Supported Cooperative Work & Social Computing*, New York, NY, USA: ACM, pp. 49–61.

Mohr, S. M. 2007. “The role of communication in knowledge management and knowledge exchange in organizations.”

Moon, M. J., and Norris, D. F. 2005. “Does Managerial Orientation Matter? the Adoption of Reinventing Government and E-Government at the Municipal Level,” *Information Systems Journal* (15:1), pp. 43–60.

Morris, R. 1994. “Computerized content analysis in management research: A demonstration of advantages & limitations,” *Journal of Management* (20:4), pp. 903–931.

Moulton, L. 2007. “Divining value with relational proxies: How moneylenders balance risk and trust in the quest for good borrowers,” *Sociological Forum* (22:3), pp. 300–330.

Myers, S. C., and Majluf, N. S. 1984. “Corporate financing and investment decisions when firms have information that investors do not have,” *Journal of Financial Economics* (13:2), pp. 187–221.

Newman, M. L., Pennebaker, J. W., Berry, D. S., and Richards, J. M. 2003. “Lying words: Predicting deception from linguistic styles,” *Personality and Social Psychology Bulletin* (29:5), p. 665.

Newson, R. 2002. “Parameters behind ‘nonparametric’ statistics: Kendall’s tau, Somers’ D and median differences,” *Stata Journal* (2:1), pp. 45–64.

Newson, R. 2006. “Confidence intervals for rank statistics: Somers’ D and extensions,” *Stata Journal* (6:3), pp. 309–334.

O’Brien, R. M. 2007. “A caution regarding rules of thumb for variance inflation factors,” *Quality & Quantity* (41:5), pp. 673–690.

Ott, M., Choi, Y., Cardie, C., and Hancock, J. T. 2011. “Finding Deceptive Opinion Spam by Any Stretch of the Imagination,” in *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies - Volume 1*, Stroudsburg: Association for Computational Linguistics, pp. 309–319.

Pavlou, P. A., Liang, H., and Xue, Y. 2007. “Understanding and mitigating uncertainty in online exchange relationships: A principal-agent perspective,” *MIS Quarterly* (31:1), pp. 105–136.

Perry, V. G. 2008. “Is ignorance bliss? Consumer accuracy in judgments about credit ratings,” *Journal of Consumer Affairs* (42:2), pp. 189–205.

Petter, S., Straub, D., and Rai, A. 2007. “Specifying formative constructs in information systems research,” *Management Information Systems Quarterly* (31:4), p. 623.

Prosper 2016. *Prosper Prospectus 2016*.

Proudfoot, J. G., Jenkins, J. L., Burgoon, J. K., and Nunamaker, J. F. 2016. “More Than Meets the Eye: How Oculometric Behaviors Evolve Over the Course of Automated Deception Detection Interactions,” *Journal of Management Information Systems* (33:2), pp. 332–360.

Qin, T., Burgoon, J. K., Blair, J., and Nunamaker, J. 2005. “Modality effects in deception detection and applications in automatic-deception-detection,” pp. 23b–23b.

Ravina, E. 2008. “Beauty, Personal Characteristics and Trust in Credit Markets,” in *American Law & Economics Association Annual Meetings*.

Richards, J. M. 2004. “The cognitive consequences of concealing feelings,” *Current Directions in Psychological Science* (13:4), pp. 131–134.

Roberts, J., and Scapens, R. 1985. “Accounting systems and systems of accountability — understanding accounting practices in their organisational contexts,” *Accounting, Organizations and Society* (10:4), pp. 443–456.

Sage, A. P. 1981. “Behavioral and Organizational Considerations in the Design of Information Systems and Processes for Planning and Decision Support,” *IEEE Transactions on Systems, Man, and Cybernetics* (11:9), pp. 640–678.

Saldanha, T. J. V., Mithas, S., and Krishnan, M. S. 2017. “Leveraging Customer Involvement for Fueling Innovation: The Role of Relational and Analytical Information Processing Capabilities,” *MIS Quarterly* (41:1), pp. 267-A11.

Serrano-Cinca, C., Gutiérrez-Nieto, B., and López-Palacios, L. 2015. “Determinants of Default in P2P Lending,” *PLOS ONE* (10:10), pp. 1–22.

Shi, N.-Z., and Tao, J. 2008. *Statistical hypothesis testing: theory and methods*, World Scientific.

Siering, M., Koch, J.-A., and Deokar, A. V. 2016. “Detecting Fraudulent Behavior on Crowdfunding Platforms: The Role of Linguistic and Content-Based Cues in Static and Dynamic Contexts,” *Journal of Management Information Systems* (33:2), pp. 421–455.

Somers, R. H. 1962. “A New Asymmetric Measure of Association for Ordinal Variables,” *American Sociological Review* (27:6), pp. 799–811.

Sonenshein, S., Herzenstein, M., and Dholakia, U. M. 2011. “How accounts shape lending decisions through fostering perceived trustworthiness,” *Organizational Behavior and Human Decision Processes* (115:1), pp. 69–84.

Stein, J. C. 2002. “Information Production and Capital Allocation: Decentralized versus Hierarchical Firms,” *The Journal of Finance* (57:5), pp. 1891–1921.

Stigler, G. J. 1961. “The economics of information,” *The Journal of Political Economy* (69:3), pp. 213–225.

Stiglitz, J. E., and Weiss, A. 1981. “Credit rationing in markets with imperfect information,” *The American Economic Review* (71:3), pp. 393–410.

TechCrunch 2016. *What Lending Club’s Falling Share Price Means for the P2P Lending Sector*. In retrieved 11. February, 2016, from http://techcrunch.com/2016/03/02/what-lending-clubs-falling-share-price-means-for-the-p2p-lending-sector/.

Ten Brinke, L., and Porter, S. 2012. “Cry Me a River: Identifying the Behavioral Consequences of Extremely High-Stakes Interpersonal Deception,” *Law and Human Behavior* (36:6), pp. 469–477.

Thies, F., Wessel, M., and Benlian, A. 2016. “Effects of Social Interaction Dynamics on Platforms,” *Journal of Management Information Systems* (33:3), pp. 843–873.

Toma, C. L., and Hancock, J. T. 2010. “Reading between the lines: Linguistic cues to deception in online dating profiles,” pp. 5–8.

Trivers, R. 2014. *The Folly of Fools: The Logic of Deceit and Self-Deception in Human Life*, Reprint., New York: Basic Books.

Utz, S. 2005. “Types of deception and underlying motivation: What people think,” *Social Science Computer Review* (23:1), pp. 49–56.

Wang, H., Greiner, M., and Anderson, J. 2009. “People-to-people lending: The emerging e-commerce transformation of a financial market,” pp. 182–195.

Weber, R. P. 1990. *Basic content analysis*, Thousand Oaks, CA, USA: Sage.

Webster, J., and Watson, R. T. 2002. “Analyzing the past to prepare for the future: Writing a literature review,” *MIS Quarterly* (26:2), pp. xiii – xxiii.

Wessel, M., Thies, F., and Benlian, A. 2017. “Opening the floodgates: the implications of increasing platform openness in crowdfunding,” *Journal of Information Technology; Basingstoke* (32:4), pp. 344–360.

Williamson, O. E. 1981. “The economics of organization: The transaction cost approach,” *American Journal of Sociology* (87:3), pp. 548–577.

World Bank 2013. *Crowdfunding's Potential for the Developing World*. In *infoDev*, retrieved 2. October, 2017, from https://www.infodev.org/infodev-files/wb_crowdfundingreport-v12.pdf.

Zhang, D., Zhou, L., Kehoe, J. L., and Kilic, I. Y. 2016. "What Online Reviewer Behaviors Really Matter? Effects of Verbal and Nonverbal Behaviors on Detection of Fake Online Reviews," *Journal of Management Information Systems* (33:2), pp. 456–481.

Zheng, B., and Agresti, A. 2000. "Summarizing the predictive power of a generalized linear model," *Statistics in Medicine* (19:13), pp. 1771–1781.

Zhou, L., Burgoon, J. K., Nunamaker, J. F., and Twitchell, D. 2004a. "Automating linguistics-based cues for detecting deception in text-based asynchronous computer-mediated communication," *Group Decision and Negotiation* (13:1), pp. 81–106.

Zhou, L., Burgoon, J. K., and Twitchell, D. P. 2003a. "A longitudinal analysis of language behavior of deception in e-mail," *Intelligence and Security Informatics* (2665), pp. 102–110.

Zhou, L., Burgoon, J. K., Twitchell, D. P., Qin, T., and Nunamaker Jr, J. F. 2004b. "A comparison of classification methods for predicting deception in computer-mediated communication," *Journal of Management Information Systems* (20:4), pp. 139–166.

Zhou, L., Twitchell, D. P., Qin, T., Burgoon, J. K., and Nunamaker Jr, J. F. 2003b. "An exploratory study into deception detection in text-based computer-mediated communication," pp. 10–pp.

Zhou, L., Yongmei Shi, and Dongsong Zhang 2008. "A statistical language modeling approach to online deception detection," *IEEE Transactions on Knowledge & Data Engineering* (20:8), pp. 1077–1081.

Zhou, L., and Zhang, D. 2006. "A comparison of deception behavior in dyad and triadic group decision making in synchronous computer-mediated communication," *Small Group Research* (37:2), pp. 140–164.

Zhou, L., and Zhang, D. 2008. “Following linguistic footprints: Automatic deception detection in online communication.,” pp. 119–122.

Ziegler, M., MacCann, C., and Roberts, R. D. 2011. *New Perspectives on Faking in Personality Assessment*, 1 edition., New York: Oxford University Press.

2.13 Appendix

The Cox PH Model

The basic Cox proportional hazard (PH) model denotes individual *i*'s hazard rate $h_i(t)$ as

$$h_i(t,X) = h_0(t) e^{\sum \beta_i x_i} \quad (1)$$

where β_i x_i describes the impact of the explanatory X variables and $h_0(t)$ describes the unspecified baseline hazard function of time (Cox 1972). As a semi-parametric model, the Cox PH model considers the ordering of failures which implies the need to handle ties (i.e. failures occurring at the same time), for which the Efron approximation is recommended (Cleves et al. 2010; Efron 1977). In our data, there are no such ties, so we do not further elaborate on this here. Extending the model for time-varying covariates is rather straightforward, and is done by allowing β_i x_i to vary with t

$$h_i(t,X) = h_0(t) e^{\sum \beta_i x_i(t)} \quad (2)$$

The Weibull Model

The Weibull model is similar to the Cox PH model, except that the Weibull model, estimated using maximum likelihood, specifies the following functional form for the hazard rate $h_0(t)$

$$h_0(t) = pt^{p-1} \exp(a) \quad (3)$$

where a and p (the shape parameter) are ancillary parameters and p>0. When p>1, the hazard increases, p=1 denotes a constant hazard and p<1 means that the hazard decreases. When we fit the Weibull model, we are therefore estimating (a, p, β'_x).

The basic idea behind parametric survival models is that the survival time (i.e. the amount of time until individual *i* defaults on his loan) follows a distribution and that the dataset can be used to estimate the distribution parameters. The Weibull model says that the hazard is either increasing or decreasing, but does not allow for a change in direction (Allison 2014). Intuitively, this strikes us as suitable for loan data. For example, assuming that individual a's hazard is likely to either increase or decrease over time and not both seems like a suitable assumption for the majority of lenders. We are therefore reasonably confident that the Weibull model adequately parameterizes the baseline hazard in our setting. We also choose this model as a robustness check, because it produces results that can be directly compared with those produced by Cox regression (Cleves et al. 2010).

Table 8 Tests of PH Assumption for Transformations of t

	Model1						**Model2**						**Model3**					
(Transform.)	Xi*t		Xi*t^2		Xi*ln(t)		Xi*t		Xi*t^2		Xi*ln(t)		Xi*t		Xi*t^2		Xi*ln(t)	
Main Effects	(rho)	(p)	(rho)	(p)	(rho)	(p)	(rho)	(p)	(rho)	(p)	(rho)	(p)	(rho)	(p)	(rho)	(p)	(rho)	(p)
Amount	-0.024	0.691	-0.047	0.430	0.004	0.948	-0.007	0.896	-0.033	0.554	0.023	0.687	-0.019	0.739	-0.041	0.465	0.007	0.901
Interest rate***	-0.231	0.000	-0.214	0.000	-0.250	0.000	-0.249	0.000	-0.230	0.000	-0.269	0.000	-0.255	0.000	-0.236	0.000	-0.276	0.000
# of bids	0.013	0.834	0.039	0.517	-0.019	0.755	0.006	0.920	0.035	0.546	-0.029	0.620	0.015	0.800	0.043	0.461	-0.018	0.754
Duration	0.101	0.091	0.090	0.136	0.114	0.057												
Credit grade*	0.085	0.095	0.075	0.140	0.096	0.059	0.110	0.027	0.100	0.045	0.121	0.015	0.114	0.026	0.104	0.041	0.125	0.014
Debt-to-income ratio**	-0.142	0.015	-0.136	0.020	-0.147	0.012	-0.124	0.038	-0.122	0.042	-0.124	0.039	-0.137	0.020	-0.131	0.026	-0.141	0.017

*** Significant at p<.01

Table 8 shows the evaluation of the proportional hazards assumption. We see that in all three models, three variables show significant interactions with the time variable (untransformed and using different transformations of time, e.g. time squared and the natural log of time). Based on the p-values, this effect is strongly significant for interest rate, significant for debt-to-income ratio and weakly significant or significant for credit-grade (depending on the model). Hence, we specify our following reported models by including a control for time interactions.

Table 9 Socio-Demographic Information

	FULL SAMPLE				DEFAULT				
Description	**Count**	**%**	**Mean**	**S.D.**	**Count**	**%**	**Def. Rate (%)**	**Mean**	**S.D.**
Occupation:									
Employee	1814	49.54			110	42.64	6.06		
Tradesman	827	22.58			82	31.78	9.92		
Retired	338	9.23			36	13.95	10.65		
Freelancer	344	9.39			11	4.26	3.20		
Managing Partner	183	5.00			14	5.43	7.65		
Civil Servant	155	4.23			5	1.94	3.23		
Other	1	0.03			0	0.00	0.00		
Gender:									
Male	2644	72.20			184	71.32	6.95		
Female	1018	27.80			74	28.68	7.2		
Age			43.08	13.40				43.86	15.92

Table 10 Exogenous Financial Information

	FULL SAMPLE				DEFAULT			
Variable	**Mean**	**S.D.**	**Range**	**Sum**	**Mean**	**S.D.**	**Range**	**Sum**
Debt-to-Income Ratio	2.89	0.91	[1,4]	10568	3.17	0.79	[1,4]	818
Credit grade	3.94	2.32	[1,8]	14426	5.02	2.27	[1,8]	1296

Table 11 Overview of Descriptives for Hard Facts

	FULL SAMPLE				DEFAULT			
Variable	**Mean**	**S.D.**	**Range**	**Sum**	**Mean**	**S.D.**	**Range**	**Sum**
Amount	9013.79	7393.83	[750,50000]	33008500	9165.70	8057.03	[1000,50000]	2364750
Interest rate	0.09	0.03	[0.03,0.18]	321.36	0.11	0.03	[.06,.18]	27.305

Table 12 Loan Related Information

	FULL SAMPLE				DEFAULT			
Variable	**Mean**	**S.D.**	**Range**	**Sum**	**Mean**	**S.D.**	**Range**	**Sum**
# of bids	17.71	14.5	[1,120]	64870	17.03	14.63	[1,103]	4393
Initial bid	548.33	488.97	[250,10000]	2008000	560.08	360.74	[250,2000]	144500
Duration	54.22	10.26	[36,60]	198552	55.54	9.36	[36,60]	14328

Table 13 LIWC results for Deception Variables of 3661 Loan Descriptions at PeerCo[32]

	FULL SAMPLE				DEFAULT			
Variable	**Mean**	**S.D.**	**Range**	**Sum**	**Mean**	**S.D.**	**Range**	**Sum**
Word count	44.24	45.99	[1,500]	161989	38.38	48.03	[1,416]	9902
Words per sentence	14.49	10.48	[0,192]	53066.94	14.17	10.94	[0,90]	3655.56
# of sentences	3.03	2.82	[0,35]	11096	2.74	3.17	[0,21]	707
Average word length	7.21	1.75	[0,43]	26397.19	7.25	2.16	[0,23]	1870.73
Unique words	36.29	32.34	[0,301]	132896	31.52	33.72	[0,272]	8132
# of 1st singular	3.29	3.80	[0,30]	12062	2.82	3.74	[0,29]	727
# of 1st plural	0.54	1.67	[0,23]	1989	0.41	1.34	[0,9]	105.02
# of self references	3.84	4.12	[0,33]	14051	3.23	4.17	[0,29]	832
2nd sing. pronouns	0.34	0.74	[0,8]	1263	0.34	0.72	[0,4]	88
Other pronouns	0.77	1.38	[0,19]	2836	0.74	1.47	[0,15]	191
Positive affect words	1.76	2.34	[0,26]	6459	1.54	2.42	[0,18]	396
# of negation words	0.32	0.75	[0,8]	1186	0.29	0.80	[0,7]	75
# of negative affect	0.34	0.75	[0,9]	1253	0.28	0.67	[0,6]	73
# of temporal words	2.67	3.48	[0,34]	9772	2.33	3.45	[0,26]	602
# of spatial words	3.51	4.30	[0,41]	12854	3.04	4.60	[0,41]	783
# of modal verbs	0.51	0.90	[0,8]	1883	0.40	0.82	[0,6]	104
# of perceptual	0.03	0.18	[0,2]	102	0.02	0.14	[0,1]	5
# of modifiers	3.18	4.18	[0,44]	11630	2.85	4.10	[0,35]	735

Table 14 Excel Results for Deception Variables[33]

	FULL SAMPLE				DEFAULT			
Variable	**Mean**	**S.D.**	**Range**	**Sum**	**Mean**	**S.D.**	**Range**	**Sum**
# of typos	1.06	1.93	[0,31]	3865	1.09	1.86	[0,14]	280
# of punctuation	6.82	8.68	[0,155]	24961	5.77	7.75	[0,58]	1488
# of emoticons	0.20	0.46	[0,4]	727	0.16	0.39	[0,2]	40
positive emoticons	0.01	0.12	[0,1]	50	0.01	0.06	[0,1]	1
negative emoticons	0.00	0.03	[0,1]	4	0.00	0.00	[0,0]	0
greeting none	0.73	0.45	[0,1]	2657	0.72	0.45	[0,1]	186
greeting formal	0.08	0.28	[0,1]	305	0.09	0.29	[0,1]	23
greeting informal	0.20	0.40	[0,1]	724	0.21	0.40	[0,1]	53

[32] Note that for the sake of comprehension, the values provided in Tables 13 and 14 are the number of reported occurrences of each measure, not the corresponding values used in the regression. The later were transformed, (i.e., standardized and divided by word count) as described in the methodology.
[33] As described on page 21, a formula was created in Microsoft Excel to count punctuation (e.g., !?,´;":.) in the text field. To count typos, the Microsoft Word CheckSpelling() function was used.

Table 15 Relevant Aspects of Interpersonal Deception Theory to the Context of P2P Lending (adapted from: Buller and Burgoon 1996)

#	Proposition	Relevant	Reasoning
1	What deceivers and respondents think and do varies according to the amount of interactive give-and-take that's possible in the situation.	no	Not the focus of our study.
2	What deceivers and respondents think and do varies according to how well they know and like each other.	yes	Anonymity should increase deception.
3	Deceivers make more strategic moves and leak more nonverbal cues than truth tellers.	yes	Implies that deceivers act strategically
4	With increased interaction, deceivers make more strategic moves and display less leakage.	yes	Implies that a single text may reveal more about deception than a conversation
5	Deceivers' and respondents' expectation of honesty (truth bias) is positively linked with interactivity and relational warmth.	no	Not the focus of our study. There is no opportunity for lenders and borrowers to form a relationship.
6	Deceivers' fear of being caught and the strategic activity that goes with that fear are lower when truth bias is high, and vice versa.	yes	Fear of being caught can lead liars to hide information.
7	Motivation affects strategic activity and leakage. (a) People who deceive for their own self-gain make more strategic moves and display more leakage. (b) The way respondents first react depends on the relative importance of the relationship and their initial suspicion.	yes	Deceivers have something to gain, as in P2P lending.
8	As relational familiarity increases, deceivers become more afraid of detection, make more strategic moves, and display more leakage.	partly	Not the focus of our study. Clearly there is a large social distance between lenders and borrowers.
9	Skilled deceivers appear more believable because they make more strategic moves and display less leakage than unskilled deceivers.	yes	Skilled deceivers may write shorter loan descriptions to avoid revealing information about their low creditworthiness.
10	A deceiver's perceived credibility is positively linked to interactivity, the respondent's truth bias, and the deceiver's communication skill but goes down to the extent that the deceiver's communication is unexpected.	yes	Perceived credibility here is provided by the loan description. The aspect of unexpected communication may be worth further study.
11	A respondent's accuracy in spotting deception goes down when interactivity, the respondent's truth bias, and the deceiver's communication skill go up. Detection is positively linked to the respondent's listening skills, relational familiarity, and the degree to which the deceiver's communication is unexpected.	yes	Similar to P4, fewer interactions can improve deception detection.
12	Respondents' suspicion is apparent in their strategic activity and leakage.	no	Does not seem applicable to our study
13	Deceivers spot suspicion when it's present. Perception of suspicion increases when a respondent's behavior is unexpected. Any respondent reactions that signal disbelief, doubt, or the need for more information increase the deceiver's perception of suspicion.	no	No opportunity for deceiving borrowers to view lender's reactions.
14	Real or imagined suspicion increases deceivers' strategic activity and leakage.	yes	Conceivable in P2P lending
15	The way deception and suspicion are displayed within a given interaction changes over time.	yes	Implies that a single text may reveal more about deception than a conversation
16	In deceptive interactions, reciprocity is the most typical pattern of adaptive response	no	Not applicable, as no repeated interaction takes place in our study
17	When the conversation is over, the respondent's detection accuracy, judgment of deceiver credibility, and truth bias depend on the deceiver's final strategic moves and leakage as well as the respondent's listening skill and remaining suspicions.	partly	Clearly leakage detection should effect lending decisions. Lenders are assumed to have reading skills.
18	When the conversation is over, the deceiver's judgment of success depends on the respondent's final reaction and the deceiver's perception of lasting suspicion.	yes	While meant for interaction situations, the underlying argument of impression formation seems to hold for P2P lending

Table 16 Weibull (Survival) Regression on Loan Default

VARIABLES	Coefficient	S.E.	t-stat.	p-value	Confidence Interval
amount	0.0001***	(0.0000)	6.5123	0.0000	0.0001 - 0.0002
interest rate	24.3160***	(4.1622)	5.8421	0.0000	16.1582 - 32.4739
number of bids	-0.0758***	(0.0117)	-6.4548	0.0000	-0.0988 - -0.0528
credit grade	-0.1024*	(0.0576)	-1.7774	0.0755	-0.2153 - 0.0105
debt-to-income ratio	0.2943***	(0.0813)	3.6185	0.0003	0.1349 - 0.4537
# of spatial words^{t}	0.9301	(0.9910)	0.9386	0.1740	-1.0122 - 2.8724
# of negation words^{t}	0.1897**	(0.1105)	1.7165	0.0431	-0.0269 - 0.4062
# of modal verbs^{t}	-0.2513***	(0.0999)	-2.5163	0.0060	-0.4471 - -0.0556
# of modifiers^{t}	0.1038***	(0.0363)	2.8563	0.0022	0.0326 - 0.1750
# of positive affect ^{t}	-0.1000**	(0.0496)	-2.0170	0.0219	-0.1972 - -0.0028
temporal words^{t}	-0.0712**	(0.0362)	-1.9667	0.0246	-0.1422 - -0.0002
no greeting^{t}	-0.9333***	(0.1735)	-5.3792	0.0000	-1.2734 - -0.5933
positive emoticons^{t}	-1.9108**	(1.0142)	-1.8841	0.0298	-3.8986 - 0.0769
ln_p	2.4456***	(0.0394)	62.0867	0.0000	2.3684 - 2.5228
Constant	-87.5678***	(3.3473)	-26.1604	0.0000	-94.1285 - -81.0071
Observations	3,661				
AIC	241.3				
Log Likelihood (Max. LH)	-105.7				

Standard errors in parentheses   *** p<0.01, ** p<0.05, * p<0.1, t=one-tailed

3. Investor Decision-Making in Equity Crowdfunding: A Trust-building Perspective

Abstract: Research suggests that the decision-making of crowd investors differs from that of traditional investors. For startups seeking funding, it remains unclear how decisions are made by the crowd. Therefore, we decided to examine how the decision-making of crowd investors can be influenced by founders of startups seeking equity investments via crowdfunding. We use an interpretive qualitative case study, examining three different cases, to gain an in-depth understanding of these elements linked to the investment decision. We aggregate and develop our findings from these cases into a model. The model consists of three core elements influencing the behavior of crowd investors: trust in the startup, the perceived risk of an investment and the received benefits in case of a positive business development. These three elements are driven by several precursors such as 'personality, expertise and shared values' for trust or the 'business model and scalability' for perceived risk. The elements strongly depend on the startup's setup and behavior. Further, external factors such as crowd herding effects or statements of opinion leaders also influence investors' decisions. The combined impact of these diverse factors can be either amplified or mitigated by the communication of the startup. The model depicts how decisions are made by crowd investors in order to help startups and crowdfunding platforms successfully approach the crowd.

Authors: This paper was written in collaboration with Dr. Dennis Steininger, Prof. Dr. Michael Woywode and Prof. Dr. Daniel Veit. With respect to the distribution of work, the following declaration can be made: The basic research idea, as well as the theoretical and conceptual model were developed by all authors, but with the lead of Andrew Isaak. The qualitative coding process was done with the lead of Andrew Isaak. Overall, Andrew Isaak is the main corresponding author of this work.

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Investor Decision-Making in Equity Crowdfunding:

A Trust-building Perspective

3.1 Introduction

In the seed phase, startups are challenged by raising capital (Schwienbacher and Larralde, 2012), often lacking collateral (Cosh et al., 2009). Crowdfunding provides entrepreneurs an alternative means of financing to traditional banks or venture capital because the crowd uses other (often soft) criteria to assess startups and the risk is shared among a multitude of investors (Schwienbacher and Larralde, 2012).

Crowdfunding changes the information flows between founders and investors. Having investors as a direct feedback channel fosters user-centered innovation and can improve products (Belleflamme et al., 2011). Additionally, Crowdfunding can also be used as a marketing tool to promote an idea or project (Belleflamme et al., 2011; Mollick, 2014) or to test market acceptance (Schwienbacher and Larralde, 2012). Thus, founders can identify problems early before wasting valuable resources (Mollick, 2014).

However, not every crowdfunding campaign is successful in raising money and awareness through the crowd. Many startups fail to receive the anticipated funding. This leads to the question as to what it takes to convince the crowd. In trying to answer this question, one successfully crowdfunded startup stated: *"In crowdfunding you don't have ultra rational VC investors, which are assessing 20 different cases per day and are totally blunted. Predominantly the crowd is comprised of private persons who can be caught emotionally" (SS_E1).* According to this presumption, the typical criteria which drive the decision-making of traditional investors do not apply to crowd investors. Especially emotional factors and trust-building seem to be particularly important in this context.

To our knowledge, only two studies research success factors of equity crowdfunding in particular (Ahlers et al., 2015; Lukkarinen et al., 2016). The authors of the first study find that in Europe, preselection of startups by crowdfunding platforms as well as the utilization of public and private networks help determine success or failure (Lukkarinen et al., 2016). Neither of these studies focus on the decision-making from a trust-building perspective in an in-depth qualitative manner. Ahlers et al. (2015) find that providing more detailed information about risks and retaining equity act as signals that strongly impact the probability of success. Contradicting the first study, social capital is found to have no significant effect on the probability of success. The authors call for research that further explores investment reasons in equity crowdfunding, pointing to the limitation of their quantitative dataset (Ahlers et al., 2015).

To obtain a deeper understanding of what leads crowdfunding projects to a successful outcome, one must gain insights on how the the decision-making of individuals within the crowd is influenced during a crowdfunding campaign. Based on this premise we investigate the following research question using an interpretive case study approach: *How can the decision-making of crowd investors be influenced by founders from a trust-building perspective and how can these influences be explained?*

The remainder is structured as follows. We first depict the fundamentals theoretical foundations of crowdfunding and the decision-making processes. We then turn to the methodology and explain the contexts of our cases. Subsequently, the results are presented and discussed. Implications for practice are drawn before we conclude with an outlook on future research.

3.2 Theoretical Foundations

3.2.1 Fundamentals of Crowdfunding Investments and the Agency Problem

With roots in the microfinance movement (Yunus, 2007; Helms, 2006), crowdfunding can be seen as a new segment of crowdsourcing. Crowdsourcing, a term that denotes the process of drawing on the wisdom of the crowd by utilizing the scale of the internet and social networks (Howe, 2006)[34], grew out of open source and Web 2.0[35] (Brabham, 2008a; Kleemann et al., 2008). In crowdfunding, the crowd provides funds to individual entrepreneurs, firms or lenders, intermediated by an online platform (Belleflamme et al., 2014; Lambert and Schwienbacher, 2010). In this process, the Internet serves as a communication platform, reducing economic frictions by providing input, monitoring and information exchange (Agrawal et al., 2011). Crowdfunding can be defined more formally as: *"the efforts by entrepreneurial individuals and groups – cultural, social, and for-profit – to fund their ventures by drawing on relatively small contributions from a relatively large number of individuals using the Internet, without standard financial intermediaries"* (Mollick, 2014, p. 2).

Founders like to raise funds in a way that is consistent with their values (Aaker and Akutsu, 2009). It is common that small amounts are crowdfunded by friends and family, especially early in the funding process (Mollick, 2014). Gerber et al. (2012) suggest that joining an online social community can motivate investors.[36] Consumers who engage in crowdfunding

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[34] More precisely "crowdsourcing represents the act of a company or institution taking a function once performed by employees and outsourcing it to an undefined (and generally large) network of people in the form of an open call.." (Howe, 2006).

[35] Web 2.0 refers to second generation websites that are designed for ease of use, while encouraging collaboration and interactivity, e.g. social network sites such as Facebook, but also blogs, wikis and video sharing sites (such as Youtube). The sites are built around user-generated content in virtual communities.

[36] According to Wang and Fesenmaier (2003), such motives include efficacy (satisfying other members' needs; being helpful to others; seeking or providing advice; sharing enjoyment) and expectancy (seeking future exchange with the project initiator) next to instrumental factors (e.g. seeking or providing emotional support, finding friends or expressing one's own identity), quality assurance (i.e. enforcing product or service excellence, product suggestions or evaluations) and status (or prestige in the community).

often want to take part in innovative behavior (Ordanini et al., 2011) while intrinsic (as opposed to extrinsic) motivations are more relevant for crowd investors (Schwienbacher and Larralde, 2012).

Four types of crowdfunding can be distinguished: reward-based, donation-based, lending-based and equity-based (Beaulieu et al., 2015; De Buysere et al., 2012).

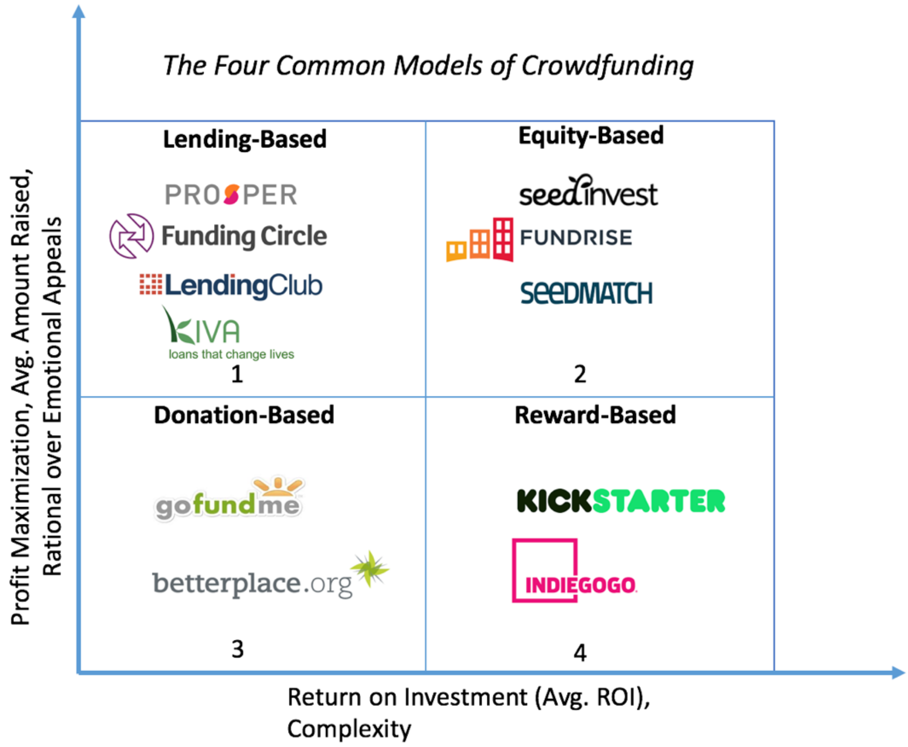

Figure 1: Four Common Models of Crowdfunding (source: author's illustration)

As depicted on the vertical axis of the figure above, these types differ in the degree that profit maximization is the primary goal (as opposed to maximizing social value or simply realizing an innovation or project) and by the amount raised. Moving upwards in the vertical direction is also accompanied by a higher degree of regulation. The horizontal axis denotes the degree that the type of crowdfunding offers a return to investors and at the same time denotes the level of complexity. However, the heterogeneity of crowdfunding types is high enough to warrant individual consideration of the four quadrants depicted.

Lending-based sites (also termed debt crowdfunding), shown in the first quadrant of the figure above, can be differentiated between those offering interest and those that do not: in the latter case, the interest on the loan can be thought of as being donated (e.g. Kiva). In the case of crowd-lending, lenders most often receive a fraction of the principal amount plus interest on a monthly basis, according to a fixed schedule (typically over 24 or 36 months). While borrowers typically seek anywhere from $10,000 up to several million dollars depending on the platform, crowdlenders typically lend in increments of $100-$500 each and may reduce their overall risk by creating an investment portfolio. This form is used by individual lenders, startups, and increasingly SMEs for medium-term loans.

Donation-based crowdfunding, depicted in quadrant three above, is philanthropic; backers typically give smaller amounts to causes they wish to support, without expecting any monetary compensation and are motivated primarily by altruism and/or the warm glow of giving (Andreoni, 1987). Donation-based platforms are often used by charities or non-governmental organisations (NGOs) to raise money for specific causes, typically social, political or environmental in nature. Donors typically receive a simple thank you mail or postcard or special mention in a video or brochure; significant donations are often met with personal invitations to cause-related events, to visit the office location of a non-profit or even the possibility to engage directly in the cause with the team or social entrepreneur.

In reward-based crowdfunding, shown in quadrant four (Figure 1), backers receive non-financial benefits for their contributions which can be intangible (e.g. the chance to participate in a project or to be mentioned in the credits of a film or music album) or tangible (e.g. to receive an early version of the product) or a mix of both. Reward-based crowdfunding thus includes a large number of projects that are de facto a type of pre-purchase (Hemer, 2011) with a relatively high risk for backers vis-à-vis other types of crowdfunding (primarily the risk of non-realization of the product by the entrepreneur). This type of crowdfunding is often employed by startups, particularly in the creative arts and in high tech B2C (Business-to-Consumer) products sector to raise $50,000 or less, with notable exceptions; very popular products are often overfunded several times over (as on most crowdfunding platforms, funding is allowed to exceed the goal set by the entrepreneur). An example of such pre-purchasing projects is the e-paper smartwatch Pebble.[37] Both reward-based and donation-based crowdfunding are lightly regulated and legal in almost all countries.

Equity crowdfunding, depicted in the second quadrant, represents the newest form of this phenomenon. Here, a plethora of online investors contribute smaller amounts in exchange for fractional ownership of a company (Vulkan et al., 2016). Startups and businesses typically seek equity funding starting from $50k all the way up to $10 million from the crowd. Some of the newest of such platforms have a sector focus, such as fundrise.com, which offers equity stakes in real estate ventures. After facing legal challenges, equity crowdfunding experienced rapid growth as legal barriers were relaxed in several markets (Ahlers et al., 2015). Examples of this are the JOBS Act in the US and Small Investor Protection Law in Germany, where equity crowdfunding has been exempted from most regulatory requirements, particularly that of making a full-fledged prospectus available to potential investors[38]; this is replaced in Germany by a three paged fact sheet (*Vermögensinformationsblatt, VIB*). The threshold amount for this requirement was raised from €100k to €2.5 million by the small investor protection law of 2015 (*Kleinanlegerschutzgesetz*). Hereby individual investors can contribute up to €10,000, a limit that does not count for professional or incorporated investors. For social projects, up to €10 million can be collected, as long as the interest rate charged is no higher than 1.5% per annum. While thresholds differ, similar regulations have been implemented in most other EU countries.

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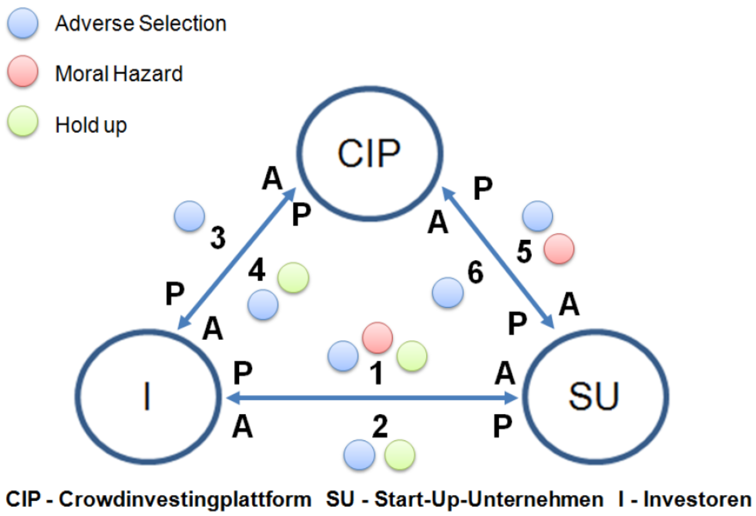
[37] http://www.kickstarter.com/projects/597507018/pebble-e-paper-watch-for-iphone-and android As accessed Aug. 30th, 2017.

[38] This was criticized by Nobel Laureate Robert Shiller (2015) for offering too little protection to online investors (or “backers”); see the Final Draft of the US Securities and Exchange Commission rules: http://www.sec.gov/rules/final/2015/33-9974.pdf

It is worth noting that both equity crowdfunding and its lending-based variety are heavily regulated (e.g. by the Securities and Exchange Commission in the US)[39].

The platform under study uses a combination of lending- and equity-based crowdfunding. To summarize these two forms, while, in lending-based crowdfunding, project owners borrow money from the crowd without traditional intermediaries (De Buysere et al., 2012) in expectation of a pre-defined interest payment as well as indirect social benefits (Lin, 2009), in equity-based crowdfunding (or 'crowdvesting' (Kortleben and Vollmar, 2012)) a company makes an open call for funding, offering equity in exchange (De Buysere et al., 2012). Investors receive shares and sometimes voting rights (Lambert and Schwienbacher, 2010). As investors, customers share the risks (Ordanini et al., 2011). Kortleben and Vollmar (2012) looked closely into the relationships found in equity-based crowdfunding, identifying several principal-agent problems, depicted in Figure 2 below.

Figure 2: Agency Constellation in Crowdfunding (adopted from Kortleben and Vollmar, 2012)



[39] Laws and policies governing equity-based crowdfunding are still developing and may limit the number of shareholders or require authorization from national securities regulators which can be prohibitively expensive (Bradford, 2012; Lambert and Schwienbacher, 2010). According to US Small Business Administration (SBA) briefing, new regulations may address this challenge: https://www.sba.gov/sites/default/files/advocacy/Issue-Brief-5-Equity-Based-Crowdfunding_2.pdf

Within the agency relation in which the investor is the principal and the start-up is the agent (no. 1), adverse selection (Akerlof, 1970; Rothschild and Stiglitz, 1976; Spence, 1973) is given because the founder has more knowledge about the company and the business plan than the investor does. Moral hazard (Arrow, 1963) occurs because the investor cannot monitor the work of the founder, who could exploit this. A hold up problem exists because investors depend on the work of the founders, which they cannot influence.

Some papers deal with the specific case of P2P-lending in which a platform intermediates between an individual borrower and many lenders (peers). Herzenstein et al. (2008) identify the need to provide lenders detailed personal information. As soft information may not be enough (Pötzsch and Böhme, 2010), independent credit grades are typically evaluated. Membership in an affinity group can also help convince lenders (Herzenstein et al., 2008). Interestingly, Larrimore et al. (2011) identify extended narratives in the project description as reducers of uncertainty for potential lenders, while the use of quantitative words can increase the chance of success (see also Herzenstein et al. (2011)). Such effects are multiplied by information cascades on the internet (Duan et al., 2009) which flow into herding behavior of investors (Prechter, 2001), often leading to or impeding funding success of a venture within a short time frame of days or hours. The goal gradient hypothesis (Hull, 1932) theorizes that the motivation to reach a goal is disproportionately strengthened as the likelihood of achieving a goal approaches. Applied to the crowdfunding setting, the theory suggests a deadline effect: that a larger amount of investors will provide funds when the targeted funding amount is within reach. Simultaneously, high funding amounts or percentages (relative to the target amount) should serve as a quality signal to investors, while low amounts serve as a warning or caution sign (Benlian and Hess, 2011; Duan et al., 2009).

3.2.2 Trust as a Theoretical Lens for the Decision-making in Crowdfunding

Developing trust within investors of the crowd is a fundamental of campaign success in crowdfunding. Moorman et al. define trust as the *"willingness to rely on an exchange partner in whom one has confidence"* (1993, p. 92). Primarily three types (or levels) of trust can be distinguished (Chen and Dhillon, 2003): system trust (Pennington et al., 2003), interpersonal trust (Rotter, 1971) and dispositional trust (Zucker, 1985). System trust depends on an individual's perceptions of the institutional environment, i.e. the structure of the system, including laws and regulations, have been found to play a significant role in online B2C transactions (Pennington et al., 2003). Interpersonal trust describes the willingness of a party to depend on another party on a personal level even if negative consequences are possible. Such trust is often formed by past experience or by the perception of commonalities with the other party (Zucker, 1985). Reputation, built by strong network ties, has been found to play a key role in funding new ventures (Shane and Cable, 2002). Finally, dispositional trust is the general trusting attitude of an individual independent of other parties.[40]

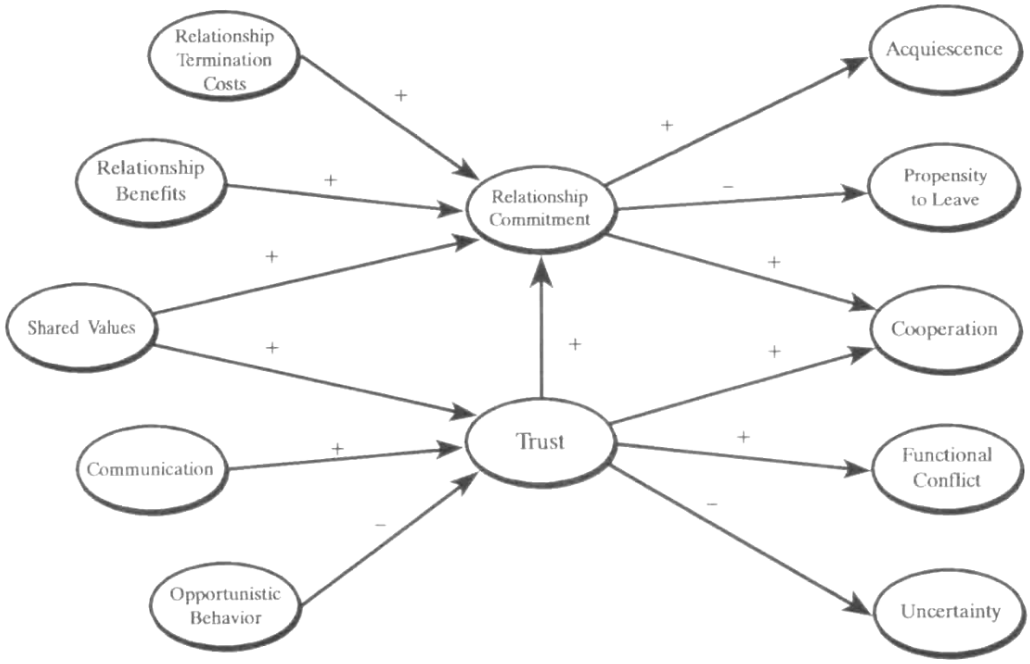
Perceived risk is a key factor influencing trust in the transaction economy (Humphrey and Schmitz, 1998; Mukherjee and Nath, 2003), especially in online settings such as crowdfunding, where founders and investors are physically separated. Risk is defined as the likelihood of an undesirable outcome (Deutsch, 1958). Corritore et al. (2003) argue that trust in online settings is also influenced by the credibility (honesty, expertise, predictability and reputation) of information on a website (i.e., how believable an information is) and ease of use of the platform. We mainly focus on interpersonal trust in this work, however, we acknowledge that this is partly mediated through the platform that hosts the campaign and the information provided by the founders on the platform. This is fundamentally different and challenging

[40] While most researchers bundle trust and distrust into a single construct, these concepts may be disjunct in the sense that they seem to evoke different sets of emotional responses: while distrust is associated with feeling fearful and anxious, trust is associated with feeling calm and secure (Kramer, 1999; McKnight and Chervany, 2001).

compared to regular offline investment processes with business angels or venture capitalists that usually meet the founder team and prepare a due diligence prior to investing.

A key trust model is developed by Morgan and Hunt (1994), who examine the coherence of trust and commitment within a business relationship as well as their dependencies on both antecedents and outcomes (acquiescence, propensity of leave, cooperation, functional conflict and decision-making uncertainty). Relationship commitment involves "*an exchange partner believing that an ongoing relationship with another is so important as to warrant maximum efforts at maintaining it; that is, the committed party believes the relationship is worth working on to ensure that it endures indefinitely"* (1994, p. 23). Support is found for a positive correlation between relationship commitment and trust, conceptualized as *"when one party has confidence in an exchange partner's reliability and integrity"* (Morgan and Hunt, 1994, p. 23). Antecedents of relationship commitment in the model are termination (or switching) costs and benefits, which are highly valuable to one party and are brought into the relationship by the other, strengthening the commitment of the former. To build trust, communication between partners should be frequent and high in quality, i.e. relevant, timely and reliable. Trust is also impacted by opportunistic behavior. Both, commitment and trust are positively influenced by the presence of 'shared values' (see Figure 3). We use this model as a theoretical scaffolding in our empirical work as suggested by Walsham (1995).

Figure 3: Model of Trust and Relationship Commitment (adapted from Morgan & Hunt, 1994)



3.3 Methodology

We utilized an interpretive, qualitative case-study approach aiming to explore and understand the learnings and insights of the people involved in crowdfunding (Sarker et al., 2012; Walsham, 1995). To ensure the quality of our approach, we followed the principles suggested for interpretive case studies by Klein and Myers (1999).

Focusing on the German equity crowdfunding market, we selected CrowdEquity, one of the biggest such platforms for startups in Europe as our meta-case. Three individual crowdfunding cases were selected by first interviewing CrowdEquity employees to detect very successful cases on the platform (Yin, 2009). Through this process, we identified *EduPlayBox*, a very successful B2C case, which seemed to be attractive to investors because of the founding team, *SimpleServ*, a B2B concept, which reached the maximum funding amount after 48 minutes, and *FeedApp*, which applied for funding on CrowdEquity twice, the first time very successfully. We explicitly chose these cases from the most successful ones that were ever run on CrowdEquity because literature suggests that B2C ideas have much higher chances to reach their funding goals in a crowdfunding campaign than B2B ideas (Gleasure, 2015; Lukkarinen et al., 2016). We wanted to gain deeper insights into this phenomenon and contrast how both types can be successful. To further our understanding on successful B2B fundings, we added the third case that was very successful in the first round but lost traction in the second funding round. This also allowed insights on the challenges and changes when running a second campaign within the same setting but with less success, rendering many of the insights from extant literature obsolete (e.g., founder composition and experience, Lukkarinen et al., 2016).

From January 2014 to February 2017 we conducted, recorded, and transcribed 22 in-depth interviews surrounding the selected cases with an average length of about 60 minutes. Within the startup context, it is common to have smaller sets of interviews since there are just not as many potential interview partners in such young environments. However, our number is well above the minimum of interview numbers found in the 'Information Systems Senior Scholars' Basket of Journals' and we reached theoretical saturation (Glaser and Strauss, 1967; Guest et al., 2006; Sarker et al., 2013).

The largest group of interview participants was investors, who mainly invested in either one or more of the case examples. To understand the phenomenon from all perspectives, heeding Klein and Myers' (1999) principles, we also interviewed employees from the CrowdEquity platform, founders as well as early-stage employees from the three startup cases, and domain experts in crowdfunding surrounding the cases (see **Error! Reference source not found.** for an overview). Additionally, we gathered a substantial amount of documents, press releases, and secondary interviews from the CrowdEquity platform for triangulation and enriched interpretations of the case contexts (Yin, 2009).

Table 1a: Overview of Short-codes for Interview Quotes

Description/Case	Short Codes	Description
Metacase: CrowdEquity	CE_E1, CE_E2, CE_E3	Experts and employees from the crowdfunding platform
Case: EduPlayBox	EB_F1, EB_F2, EB_F3	Founders
Case: SimpleServ	SS_E1, SS_E2	Early stage employees
Case: FeedApp	FA_F1, FA_E1	One founder and one early stage employee
Expert	FX	Crowdfunding expert
Investors	I1, I2, I3, I4	Investors that invested in some or all of the cases

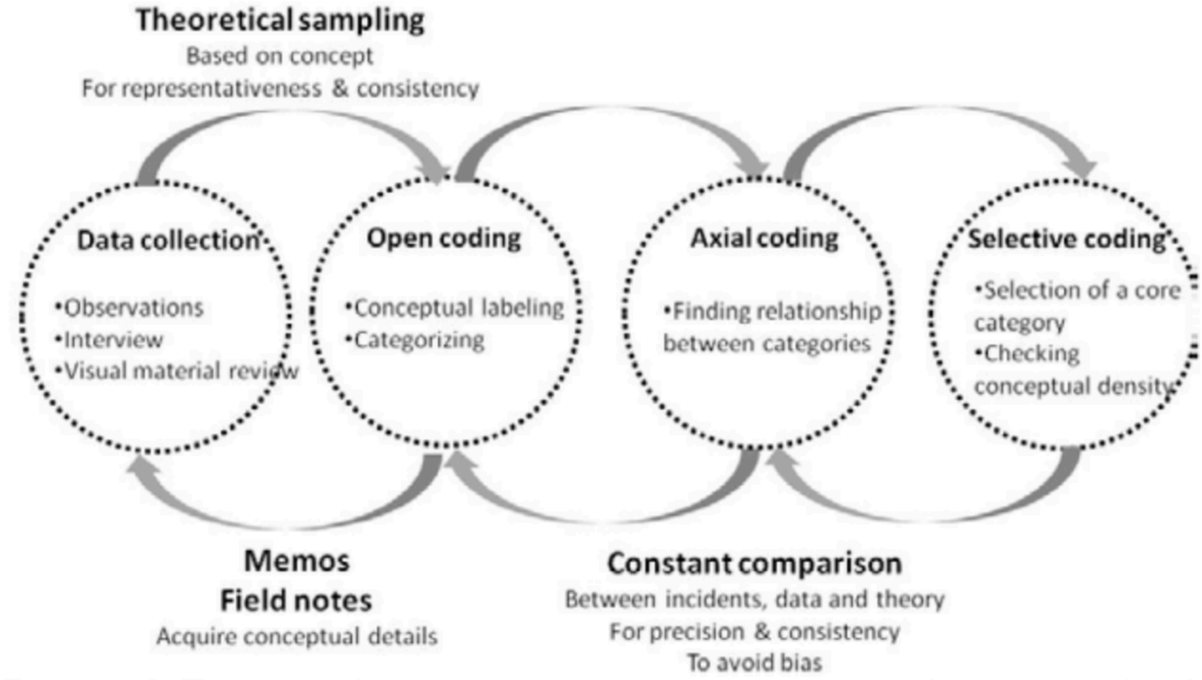
Table 1 Overview of the Interviewees

Code	Category	Company	Length (min)	# of Int.	Position	Sex	Age	Degrees	Interview Date
S1	Platform	CrowdEquity	60	1	Dealflow Manager	male	38	MSc Finance (MIT)	15.01.14
S2	Platform	CrowdEquity	60	1	Dealflow Manager	male	34	MA Economics (Potsdam)	15.01.14
S3	Platform	CrowdEquity	60	1	Head of Marketing	male	29	BSc Management (TU Dresden)	20.01.14
TB_F1	Founder	EduPlayBox	60	1	CFO	male	31	MA Industrial Engineering (HTW, Berlin)	27.01.14
TB_F2	Founder	EduPlayBox	30	1	Chief Creative	female	45	MA Art (TU Berlin & UdK Berlin)	19.04.14
TB_F3	Founder	EduPlayBox	60	2	CEO	male	47	MA Public Administration (Harvard)	15.04.14
FX	Founder	LottoOnline	75	1	CEO	male	38	MA Digital Communications (UdK Berlin)	30.01.14
PN_E1	Founder	SimpleServ	45	1	Co-Founder	male	30	MA Management (University of Innsbruck)	09.02.14
PN_E2	Founder	SimpleServ	30	1	Co-Founder	male	29	MA Management (Leuphana/Lüneburg)	20.04.14
HO_F1	Founder	FeedApp	45	1	CMO	male	28	MA Industrial Engineering (Karlsruhe/KIT)	29.03.14
HO_E1	Founder	FeedApp	60	1	CEO	male	25	BSc Business Informatics (KIT)	10.05.14
I1	Investor	n.a.	45	2	Freelance Consultant	male	34	BA Marketing (Technical School, Görlitz)	03.02.14
I2	Investor	n.a.	75	2	Consultant/Guest Speaker	male	44	MBA Management (St. Cloud State University)	01./02.02.14
I2	Investor	n.a.	45	1	Freelancer	male	27	MA Industrial Engineering (KIT)	12.04.14
I4	Investor	n.a.	60	1	Partner	male	45	PhD Computer Science (Freiberg)	13.05.14
Total			810	18					

Notes: Age backdated to time of interview; Interview with LottoOnline Founder used purely as additional background information

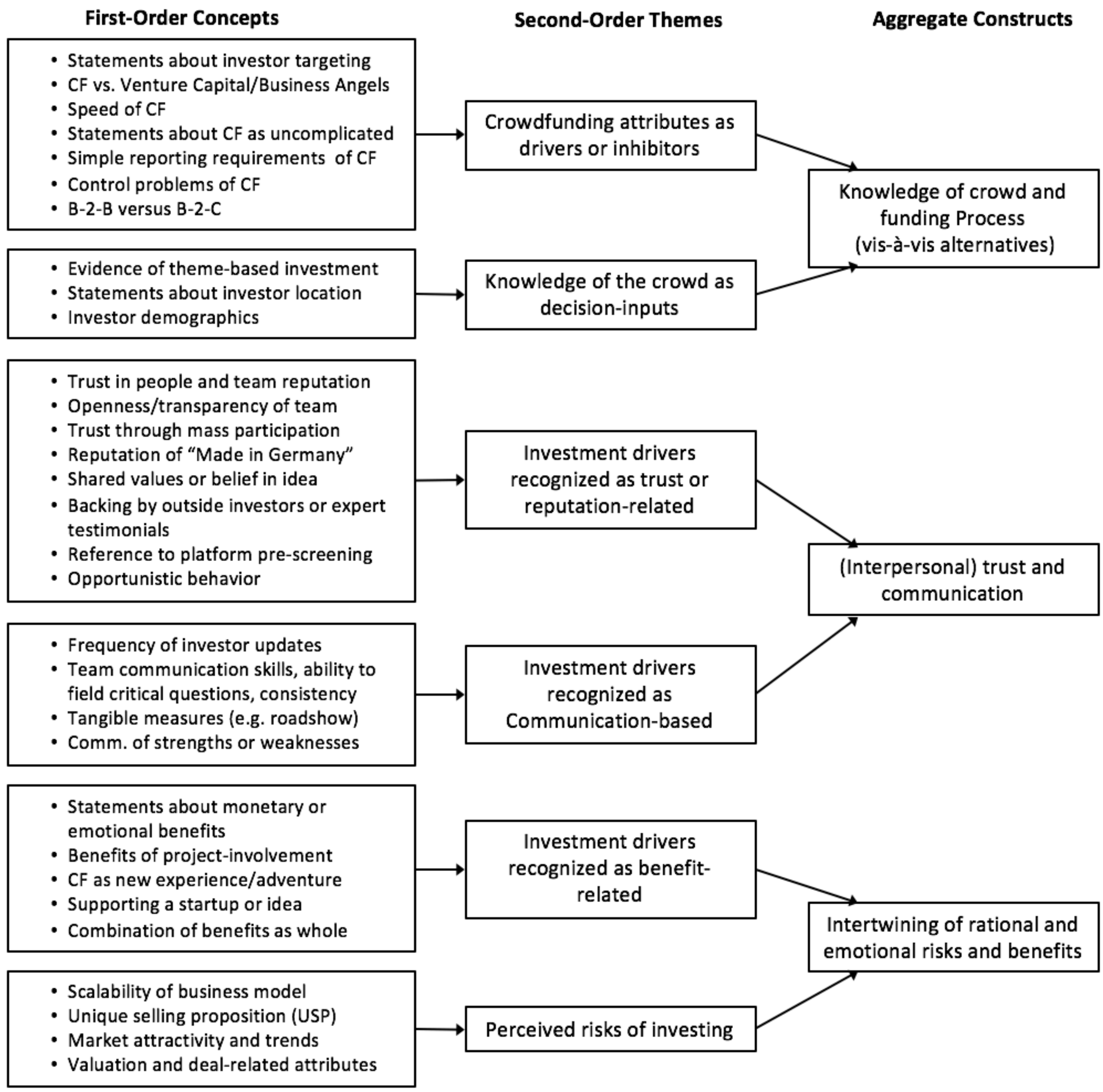
Interviews and data analysis were conducted iteratively following a grounded theory approach and the coding principles of Corbin and Strauss (6C paradigm); The main concepts of extant trust and crowdfunding literature were used as a scaffolding (Walsham, 1995).

Figure 3: Coding Process of Grounded Theory, adapted from Cho & Lee, 2014



Open coding was conducted first, letting the data speak. Next, open codes were grouped into meaningful categories during axial coding. Finally, during the selective coding process, categories were brought into relation to each other, forming higher-level concepts (Corbin and Strauss, 1990; Glaser and Strauss, 1967; Orlikowski, 1993).

Figure 4: First and Second Order Themes and Aggregate Constructs



Based on the trust/risk literature and the information received on the CrowdEquity platform, open questions were developed as guidance for the interviews. They were conducted by several interviewers. Since the interpretive case study approach is iterative and it is important to stay open, data was coded iteratively and questions were revised and discussed by the authors/interviewers constantly according to the findings of the previous interviews (Glaser and Strauss, 1967; Walsham, 1995).

To ensure the quality of interpretation and results, we built the principles of Klein and Myers into our research process as already briefly mentioned above. Details and examples of how this was done can be found in Table 2 as suggested by Ellway and Walsham (2015).

Table 2 Application of Interpretive Principles (adapted from: Ellway and Walsham, 2015; Klein and Myers, 1999)

PRINCIPLE AND DEFINITION	EXPLANATION AND EXAMPLES OF HOW PRINCIPLE WAS UPHELD
1. **Hermeneutic circle** – all human understanding develops through iteration between considering the interdependent meaning of parts and the whole that they form.	We conducted a number of iterations through the application of the supporting principles. For example, between platform experts insights for one of the specific cases and their experiences from others funding projects. A further example iteration included a comparison of interviews from the different cases in various functions, and their subsequent interpretation when contextualizing them within the social setting of the funding projects.
2**. Contextualization** – to ensure that readers can appreciate how the existing situation arose, there must be critical reflection of background of the investigated setting.	We gathered a substantial amount of data (besides the interviews) surrounding the investment process on the CrowdEquity platform and the three case histories was gathered, analyzed, and presented. Through the application of principle 6, multiple interpretations further helped us to develop an understanding of the uniqueness of the social context of each specific funding project.
3. **Interaction between the researcher and subjects** – the social construction of data achieved through interaction between researcher and subjects must be reflected upon.	Interviewees' opinions about specific funding projects were sought, but this was supplemented with real data from the funding process and the funding website on the platform. Critical readings of constructed data and discussion between researchers enabled reflection upon the data. Further reflections and discussions were triggered by adapting the interview guidelines to challenge first interpretations of earlier interviews in later ones.
4. **Abstraction and generalization** –idiographic details that emerge from interpretation of data must be related to broader theoretical concerns about the nature of human understanding and social action.	The interpretation of the interviews was situated in the context of the specific case and the meta-case. We constantly compared insights from interviews and analyses particularly through the sensitizing concept of trust. To enable generalization, we compared and contrasted between the insights from the different cases.
5. **Dialogical reasoning** – researchers must recognize the possibility of inconsistencies between theoretical	A key theoretical preconception concerned the targeted type of market: We started our case selections and interviews with an understanding that funding projects targeting B2B markets could not be very successful in running crowdfunding campaigns. However, our iterative approach and

preconceptions that guided the research and the findings that emerged with various cycles of revision.	case selection through interviews with platform experts sensitized us to the fact that this is an oversimplification in existing research and B2B funding projects might be very successful as well. However, further revision cycles and an adapted interview guideline revealed that this success might be dependent on many aspects and issues surrounding the specific case. However, extant theory on trust and the notions of the universe of discourse and universe of the undiscussed also helped to draw our attention to aspects of the case contexts that were present or absent in narratives by supporting our initial interview guide development.
6. **Multiple interpretations** – researchers must be alert to potential differences in interpretations from participants concerning narratives or stories.	We sought opinions from multiple perspectives through interviews with investors, founders, employees, and platform experts. Their interpretations on specific events and situations within the funding process were constantly compared and contrasted throughout the interviews and analyses to enable an understanding of espoused theories and theories-in-use. This was further facilitated by comparing interview data to funding project data gathered from the platform.
7. **Suspicion** – researchers must be mindful of possible biases or distortions in the narratives produced by subjects.	Critical readings of the narratives constructed by the interviewees were performed, firstly by recognizing the notion of the universe of the undiscussed, secondly by comparing them to collected documents and numbers of the funding process and discussing inconsistencies in different interviews and thirdly by acknowledging the context within which they were formed.

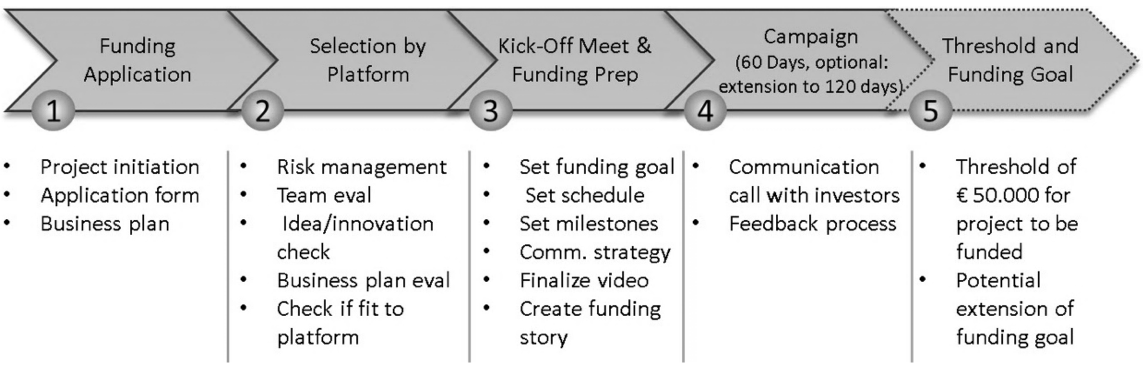
3.4 CrowdEquity as a Metacase

On CrowdEquity, young, innovative enterprises receive access to equity investments from private micro investors, i.e. the crowd. As compensation, lenders receive a share of profits and a small interest rate after the minimum contract duration (normally five years). At this period, the investment amount is paid out.

CrowdEquity focuses on scalable, innovative and sustainable business models with a first 'proof-of-concept'. The business idea is presented on a project page, containing a video and a description of how it works, the business model and the unique selling proposition (USP), the team, the project status-quo, goals, what is planned to be done with the money collected and an analysis of strengths, weaknesses, opportunities, and threats (SWOT analysis). Every startup must offer at least one ‘goody’ to the crowd, which is received when investing a certain threshold amount. Registered users have access to a closed area in which they can communicate with the founders, the so-called ‘investor’s channel’. They also receive regular updates, business plans, and sample contracts for potential investments, and can see which of the users invested how much in a project (users can remain anonymous by selecting a user name). Investors cannot communicate directly but receive additional material and regular progress reports. CrowdEquity encourages users and investors to promote the startups within their network, helps startups advertise their funding (CE_E3) and offers the opportunity to hold an ‘investment call’, an online Q&A session with the crowd.

Every campaign has a funding threshold – as soon as it is reached, the contracts go into effect, which means that the project is funded with the minimum required amount. Every project has a funding limit, which closes funding automatically when reached. Since May 2013, startups have the opportunity to raise the funding limit multiple times. This artificial shortage helps startups stimulate investments (CE_E3). Figure 6 below summarizes the funding process of CrowdEquity.

Figure 5: The Campaign and Investment Process on CrowdEquity



3.5 First Startup Case: EduPlayBox

EduPlayBox is an explorative game box for kids aged four to ten years, which is delivered once per month on a subscription basis. It is grounded on the concept of 'learning through playing': child development is fostered simply through play, without any learning pressure. Every box contains three different exploration games, materials and instructions, tips for parents about educational play, a story to read out loud and an audio CD so that parents have some time for themselves. Boxes can be ordered on the website of EduPlayBox for a monthly fee of € 19 to € 22,90 (VAT included) depending on the chosen cancelation period. Costs of the firm are € 10 for packaging and materials, resulting in a contribution margin of € 6 to € 9,24 (VAT excluded) per box. The business model is based on the accumulation of these contribution margins through the subscription model and success is strongly contingent on the customer lifetime, which needs to compensate for the cost of customer acquisition.

EduPlayBox raised € 600.000, starting with a minimum funding threshold of € 50.000, reached after only 29 minutes, and a limit of € 300.000, reached after about 35 hours. The limit was increased twice, first to € 450.000, reached after about a week and then to € 600.000, reached after one month. 599 investors invested, resulting in an average investment of nearly € 1.000. Many investors invested more than once and increased their funding over time. About 70 investors contributed more than the € 2.500 threshold and were thus invited for one of the EduPlayBox 'investor's dinners'.

3.5.1 The Founding Team

The founders of EduPlayBox, a couple as well as two others produced and developed the EduPlayBox. The female of the couple, who invented EduPlayBox, develops the contents of new boxes. She worked for six years as a consultant at one of the top consultancies and five years as a product manager for television. Afterwards, she helped found and lead several private schools as their director. The male of the founders' couple, the CEO of EduPlayBox, previously co-founded one of the largest online toy stores. As a CMO, he led the acquisition of over 300.000 new customers annually. Before that, he worked for four years as a consultant at one of the top consultancies and after his exit from the toy store, he successfully founded another internet firm. The CFO of EduPlayBox previously co-founded an online music video service and a translation service for web videos. Before that, he worked for one of the largest auditing firms and for the financial services in a large automotive manufacturer. The forth founder is Chief Operating Officer and responsible for procurement, logistics and customer support. She previously worked for four years as the project manager of the chairman of one of the largest pharmaceutical corporations.

3.5.2 EduPlayBox: Crowd Investor Decision Drivers and Trust-building Mechanisms

EduPlayBox is based on the two topics 'education' and 'children' that seem to attract a lot of investors, especially those that have kids themselves*: "Many of our [crowd] investors are motivated by the topics 'education' and 'children'. Several investors have many kids"* (EB_F3). Another EduPlayBox founder (EB_F2) remarked: *"During the [investor] meal we really noticed that a lot of investors were highly motivated by the idea and by contributing to education – a socially important topic"*.[41] The attractiveness of the idea and product was also confirmed directly by investors: *"[As a goody] we got one of the boxes. In my case that was really good because we have a daughter in the age bracket and my daughter liked it a lot" (*I4). The intrinsic motivation of the founders to support the development of children convinced one investor: *"Mrs. [founder couple] seems to be really attached to it [EduPlayBox] and it seems*

[41] The couple outlined these facts in an interview on YouTube: *"The idea of EduPlayBox convinced people. It is a huge success because it meets the needs of the people and it wants to change society. It is about education and changing the learning culture. So the mix of economic potential and potential to change society...convinced people"*.

to be her life. These are really good premises" (I2). In addition, one investor was impressed that EduPlayBox was actually founded by a family (I1).

Besides that, the team itself seemed to play an important role for investors: "*Before EduPlayBox, [the online toy store] was kind of a precursor [the male couple founder] and also his wife […] previously founded a school. The EduPlayBox guys were clearly on top of things. [The couple], I guess, come from a consulting background and [...] their appearance was very competent*". (I1) Especially [the male part of the founders couple] with his previous experience was mentioned several times as a decision criterion (I1, I2, I4, CE_E1).[42]

Further, a CrowdEquity employee (CE_E3) explained that the founders' network plays a key role: *"[It is problematic] if there is not a crowd in the beginning which invest on a large scale. Therefore, we tell startups that, if they know [interested] people, they should get them to invest at the start of the funding to signal trust to the crowd*". The EduPlayBox team followed this advice. One founder estimated the amount provided by their own network as about 17-20% (EB_F1) and another added: "*I believe [using one's own network] plays an important role insofar as a lot of our acquaintances decided to invest on the first funding day or in the days directly after so that the money came together fast […] that presumably led to observers [in the crowd] getting the feeling that if so many are investing now, then this must be a good team or offer*" (EB_F3). This herding effect was also brought forward by EB_F1 and confirmed by CE_E1: "*It is important that there is strong investment activity in the beginning because a herding mindset predominates [in the crowd]*". He added that herding convinces undecided investors in particular.

42 *"Above all, the founding team of EduPlayBox convinced me because one of the founders, whom I know personally, is very successful with [an online toy store], which means he knows the market for children and toys and has proven successful in this field. That's the crucial criterion for me"* (I4). One investor (I2) said: *"I believe that [this founder] had a very strong influence […] [and] that many investors trusted in his previous success".*

The team of EduPlayBox approached all kinds of channels in their network - personal acquaintances, Xing, LinkedIn, Twitter and Facebook (EB_F2, EB_F3). They pointed out that no single channel is most important in crowdfunding because of crowd heterogeneity. Regarding Facebook one founder remarked: *"Of course […] Facebook is the largest. There you can reach a lot of people […]. I am a communicator with 1500 plus friends on Facebook; I managed the community [of EduPlayBox on Facebook] with about 26.000 fans back then. Today we have about 56.000"* (EB_F2). This quote illustrates the extensive network of the EduPlayBox founders. In addition to their own endeavors, CrowdEquity supported EduPlayBox with their own social media activities (EB_F1).

Several investors were also very impressed by EduPlayBox's business model presentation on CrowdEquity (I1; I2; I4). EduPlayBox described it (EB_F3): "*We tried to show that this business model has economic logic. Through subscriptions, which cumulate small income streams over time, profitability is based on subscription lifetime. We were able to show impressive growth figures from our first four months, a clear indication […]. I think this combination – idea and comprehensible business model – makes sense for laymen [...]"*. One investor (I4) emphasized that he was convinced by the realistic approach of the business plan without any daring assumptions or exaggerated numbers. Another one added (I1): "*If you see them calculate on a cent level what a box costs and what you can earn through it with lifecycle, etc. then you get a good feeling. The idea […] they looked into it in depth. The presentation of the numbers was convincing*". One founder (EB_F1) commented: *"[…] you have many unprofessional investors [in crowdfunding], you can say that colorful, beautiful, understandable, aesthetics, etc. work the best here"*. One convinced investor (I1) agreed: "*I am quickly impressed by beautiful graphics. Some startups value highly that their SWOT matrix is pretty, that the numbers, the charts look good and the text is well processed. That impresses a lot*".

According to CrowdEquity employees, the video on the project page plays a very important role in investor decision-making (CE_E1, CE_E2, CE_E3). That coincides with the statements and experience of the EduPlayBox founders. We asked a crowdfunding expert (and also founder) about the relevance of the different elements on the project page on CrowdEquity, who responded: *"I would say the video weights about 80 % - I am pretty sure. I still know [the influence of moving images] from the online-marketing […], the investment increases proportional to video views"* (FX). One of the founders emphasized the importance of the first seconds of the video: *"I believe the first 20 seconds are most important […] many people do not even watch it to the end [...]. Either you attract people or you do not [...]. In TV series, you can advertise but the first impression needs to excite people and that is the same on CrowdEquity [...]. From different people, especially from our friends, we got the feedback that the video was brisk and convincing, although it is unprofessional and self-produced. Therefore, the video has a very high influence on the decision"* (EB_F3). EB_F1 also sees an important role in the revenue statements of the couple's male founder: *"...I guess 30 or 40 % of the video's success led back to [him] and his statement [about how EduPlayBox earns money] because it is just a huge trust factor. He already understood e-commerce for children and is trying it again. You buy that - the video is also beautiful"*.

The investor dinner also influenced the success of EduPlayBox. One investor (I1) said that he liked that the founders made themselves tangible for investors and mentioned it as a trust-increasing factor. I1 was angry afterwards that he had not raised his investment to over € 2.500 to be part of one of the dinners. EB_F3 confirmed: "*the reactions were very positive. Investors were excited and happy to meet the founders and we got very positive feedback on it"*. One founder (EB_F3) emphasized his belief that some investors raised their investment again just to qualify for participation in one of the dinners and that this offer was successful. A participating investor summarized: "*[In the investment dinner] it was great to meet the founding* *team but also various other interesting participants… I would recommend it and think it is an awesome idea as a complement to the goody*" (I4).

Concerning the communication with investors one of the interviewees (I4) said: "[That is something [which] stuck me, the communication [of EduPlayBox] was extraordinarily good. For every question, regardless how short there came a detailed answer […] very positive because they continued this also after the funding. Even today their communication is very quick, comprehensive and very open". The responsible founder for investor relations at EduPlayBox (EB_F3) reflected: "*…I got the feedback from CrowdEquity […] that our comprehensible, detailed and respectful explanations when answering questions created additional trust. In the end, the crowd is investing and investments are always a trust topic. I invest with a large risk, try to reduce uncertainties and if the [team] behind the idea makes an experienced and professional impression then the [perceived] risk factor is reduced*". This was confirmed by another investor (I2): "*I dived deeply into the topic and asked a lot of questions to [the male part of the founder couple]. Also unpleasant ones, which he answered openly, impressing me*".

3.6 Second Startup Case: SimpleServ

SimpleServ develops and produces what they call 'the world's simplest server', the 'SimpleServ-Box', directed at small and medium-sized companies and private households. The product has just one button and a one-page instruction sheet. It is designed to protect users from dangerous data leaks and security flaws. With a SimpleServ-Box, users keep all their data on their own server at home or in the office, while at the same time having the possibility to collaborate from everywhere and to share data through their own cloud. The box consists of up-to-date hardware 'Made in Germany' and an extensive software package. SimpleServ also provides their own social network for the SimpleServ-Box, a content management system, a browser-based collaboration interface and specially designed applications, such as a team calendar. It also allows for third party apps.

The team positions the SimpleServ-Box as a high quality product on hardware, software, security, design and service. For the future, the startup plans to offer a SimpleServ-Box version for private households, premium service contracts, mobile apps, wireless repeaters, and software licenses for other hardware providers. The main revenue stream of SimpleServ is the sale of the SimpleServ-Box for € 2.149[43]. When the firm began looking for funding, they had already provided a first proof of concept by selling 46 units to early adopters.

When SimpleServ funding opened it took exactly 48 minutes until the funding sum of € 200.000 was reached (SS_E2). The funding threshold of € 50.000 was collected after only six minutes, € 100.000 within twelve minutes. 220 people invested, with a funding average of about € 909.

3.6.1 The Founding Team

The current CEO and original founder of SimpleServ previously worked for several companies including a large online portal and one of the leading professional social networking sites (SNS), developing accounting, inventory, and ERP systems. During his time at the SNS, he met the second founder. Today both are responsible for software development. The second founder previously started a file sharing service at age 16, studied marketing and management, and worked for some time as a freelance developer before going to work for the SNS where he met his co-founder and the first prototypes of the SimpleServ-Box were created. During the crowdfunding campaign, three more employees joined SimpleServ.

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[43] The 2016 price range is from €1511 (entry-level box) to € 5998 (with 18 Terabytes of storage). Hardware costs are well below these amounts, with the contribution margin the highest for the top model.

3.6.2 SimpleServ: Crowd Investor Decision Drivers and Trust-building Mechanisms

Two investors (I1, I2) were attracted by data security, sovereignty and innovativeness of the product. *"Internet security was a huge trend",* explained one investor (I2). SimpleServ tried to emotionalize the topic by storytelling: *"We can tell people 'Hey, it's all about your data sovereignty and that you really own the data' and then they notice 'Yes, that's true! I like that!' "* (SS_E1*).* One of the CrowdEquity employees said: *"They [SimpleServ] told a cool story in their video - story-wise they are really good. They build a boring product an enterprise server but sell it as the 'simplest server of the world', with the cloud on your own server at home […]. THE answer in the age of the NSA and the uncertainties of the cloud […]. And you have to watch the video and see how the story is told! The founder […] is absolutely inspiring, really well done with some humor that causes investors to really like the startup"* (CE_E3). SS_E1 explained that the story is an important reference point for people to remember.

By conveying emotions, one can (partly) circumvent the cognitive selection process: *"In crowdfunding you don't have these super rational VC investors who check out 20 different cases per day and are totally serious, but rather private people whom you can catch on an emotional level. When approaching a [professional], number-oriented investor, it is an art to catch him off guard with emotions. Private people, who just decide 'Ok, I have some play money', are a completely different story"* (SS_E2). This explains the importance of the video: *"With a video one can transport distinctly more emotions and authenticity – a unique opportunity!"* (SS_E2). Investors want to lean back and relax and therefore prefer a convincing, easily consumed, video (SS_E2). I1 also confirmed the impact of the video: "*I was really impressed by the story and the film was the door opener*". SimpleServ presented themselves professionally overall (CE_E3): *"The presentation had this strong pull like the keynotes of [Steve] Jobs. Likeable, focused and prepared […] and you enjoyed being gripped by the story"*, one of the investors recalls (I1). The comparison to Apple is also made by a CrowdEquity employee: *"…their' appearance is like Apple, all people work with the same mindset - from marketing to the product - and not: one is building the product while the other is selling it*" (CE_E3).

However, in communication with investors, SimpleServ employees (SS_E1; SS_E2) noted improvement potential: "*We didn't have a large PR agency back then. I would definitely change that next time because press coverage distinctly increases the probability of success and therefore also the chance that it really takes off […]. We talked to people who wanted to raise € 100.000 on Kickstarter but accidently got ten million and in all the conversations they stressed that it was essential for their success that they did massive PR in the months before the start*" (SS_E2). The reason, he argues, is that with so much PR, hundreds of people are already convinced and will invest within the first hours.

Funding still went very quickly (I2). Investors needed to decide quickly before the funding limit was reached. In addition, the business plan was not provided until the funding start so that nobody was able to read it beforehand (SS_E2). Therefore, investment decisions were more *"reflex decisions"* (I2). Still, the investor stating this said that he was sure about his investment decision (I2). This was confirmed by I1 who said that he would normally take more time to decide but was already fully convinced about SimpleServ and waited impatiently for the start.

The SimpleServ-Box goody substantially influenced funding: "[Funding went incredibly fast] because we offered this goody. We told investors that they would receive a box if they invest more than € 2.000. An amazing deal […] on purpose…it accelerated our funding immensely" (SS_E2). Another employee (SS_E1) pointed out that this was especially attractive to early adopters, who received the product at a discount. One investor said: "The box was cool regarding its look and feel and the well-designed surface" (I1). Some investors want to be among the first to support a company (SS_E1) and are proud to be involved in funding and business development: “The people write […] ‘Yes, I invested, I invested in SimpleServ!’. The people are proud about it” (SS_E1).

Many investors initially wanted to invest less in SimpleServ, but then decided to raise their amounts to get the box (SS_E2). 55 investors invested € 2.000 or more to receive a SimpleServ-Box. I2 added: “[In SimpleServ] investors invested quite a lot on average. If the funding sum is high and only few investors invested so far but the funding limit is nearly reached, then this is a good argument for me to invest”. The SimpleServ-Box as a goody also had a marketing effect: *“Every box in the market does marketing for us.'”* (SS_E2). Because of this boosting effect, SS_E2 said that SimpleServ would use the Box as a goody again, which evidently turned out to be a good decision.

The team also played an important role for investors (I1): “*I was really impressed by their whole appearance and commitment to the product and the idea”* which was supported by I2. Further, the team’s experience (I1) and successful business development (CE_E3) were outlined. SS_E2 remarked: *“Because the whole team was convincing, especially the founders I guess. Especially [the first founder], is very charismatic and natural”*. This was also confirmed by both SS_E1 and CE_E3.

The team also used their own social networks to boost success: “We called all our acquaintances and friends, telling everyone 'come to CrowdEquity', tell all your friends, invest yourself because we didn't know if [the campaign] would be successful or not” (SS_E1). They used all available social media channels to communicate with potential investors (SS_E1; SS_E2). For the funding begin, SimpleServ created a Facebook event and invited everybody from their network (SS_E1). I1 pointed out that SimpleServ is well connected in the region they are located in and that they are very apt at Internet-related communication and networking. Their post-crowdfunding communication effort was also praised: “*I also liked the* *communication policy of SimpleServ a lot, who record update videos from the founder from time to time. I was very attracted by this.*" (I2).

3.7 Third Startup Case: FeedApp

FeedApp enables firms to receive fast and anonymous feedback from their customers via smartphones. The end user can provide feedback to firms in the following ways: by scanning a QR code or entering a short-URL provided by the feedback-seeking company, via a smartphone app, via near field communication NFC) or SMS. If the target firm is not an FeedApp customer, the feedback is forwarded to the firm anyway. This is part of FeedApp's sales strategy. Giving feedback is free for end-users. Participating firms can put up posters, table displays or add information on the receipt to advertise the mechanism. The feedback is sent in real-time to a web surface, which allows administration of the comments and responding to critique via the FeedApp messaging-system.

Customer satisfaction and loyalty can be increased significantly through direct contact between the end-user and the firm's chief executive as well as via the possibility for companies to send coupons to customers. FeedApp can also deliver context information e.g., at which table the feedback providers were sitting to identify location-based problems. Business customers pay a fixed fee per month to FeedApp depending on the scope of service plus a one-time set-up fee. During the first CrowdEquity funding, FeedApp offered a three month (paid) trial period.

On the first day € 63.500 were raised. The funding threshold was reached after two weeks. The normal campaign length is two months, which was extended. The funding limit of € 400.000 was not reached after the campaign duration of four months and funding closed with a sum of € 160.000 with 245 investors involved, resulting in an average investment of about € 653.

3.7.1 The Founding Team

FeedApp was founded by four former students from a technical university, two industrial engineers and two computer scientists. The team combines expertise in software development, marketing, finance, and sales. With the investments from the first CrowdEquity round, FeedApp was able to hire additional employees to grow the firm.

3.7.2 FeedApp: Crowd Investor Decision Drivers and Trust-building Mechanisms

In this case, the business idea also played a large role. One investor (I3) explained: "*I am backing the idea of FeedApp because I find the goal they are following really desirable, that is customer feedback and honesty as values*". I1 and I4 also invested because they were convinced by the idea, which was very important for FeedApp (FA_E1). However, according to FeedApp, the B2B business model was also a problem: "*We think it is a big problem that many of the people which participate on crowdfunding platforms are private investors that invest predominantly in consumer products, since it is easier for them to understand the business model. Complex business models, encountered in B2B relations, are much harder to illustrate. They are simply not as sexy, lack the herding effect you encounter with all these cool products, which - in the best case - you can even buy and use for yourself*" (FA_E1).

FA_E1 argued also that viral spreading is much higher for B2C products. CrowdEquity added: "*Mostly B2B topics, to be honest [have difficulty getting funded]. There is the investor that is B2C thinking at home on the couch. You have to make them aware of the problems of a B2B provider [...] And the task is to show good testimonials, which essentially say 'yes, we use it and it is so good, that we are satisfied'*" (CE_E3). That is what FeedApp tried when including their famous business angel in their investment story and their video.

The importance of the video especially in B2B was outlined by the interviewed FeedApp employee (FA_E1) who said that it helps investors understand the product. One of the investors called the video presentation very powerful (I3). I2 liked the video and how it illustrated the product. However, the video was an element in which one of the founders saw an issue: *"We produced a video in which we also described which negative experiences we made. These lead to doubts and that is a mistake, which I wouldn't repeat. We were too honest I guess"* (FA_F1).

The 'negative experiences' addressed in the video were about customer acquisition and PR and the readjustment of their target group (FA_F1). This led to changes in the business model and new billing structures. FA_E1 sees one reason for the less successful second round on CrowdEquity in these changes: *"Cash flow changed because we introduced a new business model and therefore [...] for investors who compared the second to the first round, it looked like we missed our targets, disastrous in crowdfunding. [Then] the atmosphere changes"*. One investor (I3) explained that although the revenue goal was hit the costs were higher than expected and therefore the margin dropped. Another investor recalled similar thoughts: "*In the second round [I was not longer attracted by the business model] because it became discernible that the [business] model and the growth rates apparently weren't that realistic or didn't occur as anticipated by the team. Further, they did this big readjustment and so I didn't invest in the second round*" (I4).

They tried to get as much as possible out of the PR hype triggered by the first round and so they used their new press contacts also for the second round in order to raise more attention: *"...we were relatively self-confident [...]. We said that it will be the largest crowdfunding, to date and resulting in a high PR impact"* (FA_E1). This strategy was not perceived as positive by every investor (e.g., I3).

FeedApp also tried to activate their personal network to accelerate funding as CrowdEquity recommends (FA_F1). One of their acquaintances (I3) confirmed that many of their personal contacts invested. In addition, FA_E2 described that beyond this, they relied on the (PR-) actions of CrowdEquity.

FeedApp offered an investor call (FA_F1), where one founder explained the plan for the next months and answered participants' questions about cash flow, turnover, customer acquisition costs, lifetime value and so forth. The questions raised by private micro investors are not really critical for the startups on CrowdEquity because investors cannot dig very deeply into the cases to assess the business model (FA_F1; FA_E1). Investors perceived the call as very positive. I2 explained that it showed that the founders back their product, know what they are doing and react sensibly to the questions raised leading him to raise his investment further.

As mentioned before, FeedApp offered their software as a goody which was not redeemed at all (FA_F1; FA_E1). The employee interviewed (FA_E1) explained that the software is only suitable for specific firms and they were not able to offer a B2C product, which could really be used by most investors. Thus, investors were not attracted by their goody (I2, I5).

The team, on the other hand, convinced most investors interviewed (I1; I2; I3). Only I4 was critical about the teams' composition due to the founders' youth. As they do not have "*20 years of professional experience in the field*", he was not sure if they would be able to predict growth.

A technical problem at the start of the second campaign had a substantial influence on the success of the second round. FA_F1 described the start and technical problems as a 'fail' because the initial funding boost was not triggered: *"You know, this is the herd effect: if you see a lot of people walking in one direction you follow. And if you don't have this effect because* *of a technical problem, it won't work [...] and the effect is exponential"*. CrowdEquity conjectured that the disadvantage was a decrease of the funding sum by about 10-20 % (CE_E3).

The other interviewee from FeedApp (FA_E1) outlined how important the first wave of investors is for the funding drive because initial investors often thrill others to invest as well. During the first funding round, FA_F1 also noticed some kind of a last minute panic – it accelerated because everyone wanted *"a piece of the cake"* (FA_F1). I3 identified these effects in his own behavior during the first round: *"I saw that the funding went relatively fast, […] and this definitely influenced me. If it had proceeded really slowly, I would have interpreted that as a lack of interest in other people who maybe even know the ropes better than me. It was an emotional action […]. I thought 'Come on'. It went really fast*". Due to the fact that the people were not confronted with herding in the second round they hesitated and waited to see what would happen before deciding (FA_E1).

CrowdEquity recommends that startups, which extend the funding period to raise attention, provide additional updates about business development (CE_E2). One FeedApp founder (FA_F1) admitted that at some point in the second round they were not able to provide more updates, which led to funding stagnation. They tried to acquire additional investors and referred every business angel they could to the platform. The importance of updates was also outlined by another interviewed crowdfunding expert (FX) who said that one should push intense PR about the funding duration for quick wins, which can be communicated to the crowd. According to him, many investors split their investment and observe how funding develops. Additional updates can trigger their investment. This idea was confirmed by investors (I1; I2).

FA_E1 mentioned another possible explanation regarding the low sum that was raised in the second crowdfunding campaign: "*Another effect possibly is that on that date there wasn't enough capital on the [CrowdEquity] platform…I think at the same time there was a startup* *which also raised quite a large sum*". CrowdEquity responded that there are clear indications that when a new project starts their funding it influences the other available projects. One reason is that new startups take over the first position on the investment list (CE_E3).

In addition, the higher funding limit was mentioned: "*In general, fundings got slower on CrowdEquity. The reason may be that the sums [which are raised] are larger. People have more time to read the plans, to think about it. For me it was the same - I first invested only the minimum amount and then waited for the [investment] call before [investing further]*" (I2). The investor added that you have more time to be critical and to question the model. This was confirmed by one of the CrowdEquity employees (CE_E1). I1 and I2 both said that they always wait until the very end with their investment to see how funding develops.

FA_F1 said that if they could repeat the second round, they would lower the funding threshold and funding limit significantly; after reaching the initial goal, they would increase the funding limit successively until reaching the truly desired sum. This is also recommended by CrowdEquity because the impact of an investor's investment looks much bigger on the investment bar (CE_E1). Further, investors are led to believe that a lot of capital was raised since their last visit.

3.8 Discussion and theoretical Implications

3.8.1 Cross-Case Comparison

Table 3 Comparison of the Cases

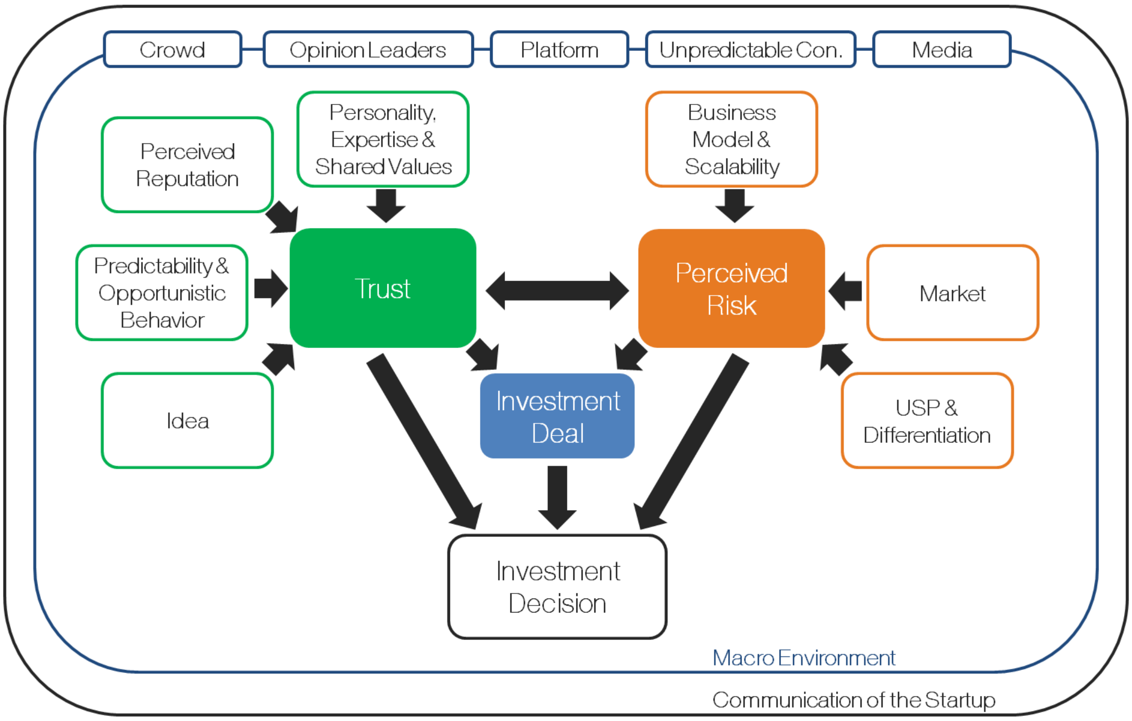
Element	CASE 1: EDUPLAYBOX	CASE 2: SIMPLESERV	CASE 3: FEEDAPP [2^{n} round]
Target Market	B2C	B2B	B2B
Amount Raised	€ 600.000	€ 200.000	€ 100.000 [2nd round: € 160.000]
Time to Reach Amount	30 days	48 minutes	3 hours [120 days]
Number of Limit Increases	2 (€ 300.000, € 450.000, € 600.000)	0	0 [0]
Number of Investors	599	220	131 [245]
Average Investment	€ 1002	€ 909	€ 763 [€ 653]
Threshold: Incentives	• € 250: Product • € 2500: Investor's dinner	• € 250: € 250 discount for product • € 2000: Product	• € 250: 50% discount for contract [€ 250: 6-month premium license]
Trust-building Mechanisms	• Investor's dinner; tangible founders • Open and continuous communication; comprehensive & respectful answers • Industry experience of founders • Social attachment to product/incentive • First investments driven by founders' network • Convincing explanation of business model in video • Impressive growth figures from first four months • Realistic business plan	• Impressive storytelling • Data security of product • Sold as answer to NSA scandal • Founder's humor, charisma and emotional, inspiring video • Apple-like branding • Team's commitment to the product and idea • Founder's previous experience • Social media competence	• Use of testimonials • Investor call/Q&A: good fielding of questions shows team expertise • Renown supporters • Video • Product associated with honest feedback • Use of press contacts and PR hype from first round, raising attention • Activation of personal networks
Trust-challenging Mechanisms	• (None mentioned)	• No use of PR agency • Very short decision windows to invest, not allowing enough time for a rational decision	• Complexity of business model • Video also mentions negative experiences (with customer acquisition and PR), creating doubt • Cash flow & business model changes from first round, creating uncertainty • Lower margins than in first round; demonstrating that initial growth rates were unrealistic • Young team = inexperience to some • Initial funding goal too high • Technical problems at funding begin slowed momentum-building • No updates in part of 2nd round

We summarize and contrast the findings in Table 3. The cross-case comparison denotes the business type (B2C/B2B), total amount raised, time it took to reach this amount, any increases in the funding limit, the total number of investors, as well as any investment incentives. Next, trust-building and trust-challenging mechanisms are compiled to facilitate comparison. While in the first two cases, trust-building mechanisms are predominant, the third case presents a balanced picture, hampered by trust-challenging factors in the second round.

3.8.2 Emerging Theoretical Framework

We discovered that two levels play an important role in investor decision-making in crowdfunding: the micro-level, which describes the direct factors on which the decision is made (i.e. the impact through the setup of the startup) and the macro environment, which represents external influences. Both levels share strong interdependencies and can be influenced by communication of the startup. These elements comprise the proposed 'Crowd Investor Decision Influence Model' that combines existing literature as the overarching framework and in-depth insights from our qualitative case studies to understand interlinks and concrete actions that entrepreneurs can take (see Figure 7 below).

Figure 7: The Crowd Investor Decision Influence Model



3.8.3 Components of the Macro Environment

The crowd: as supported by the conducted case studies, the crowd highly influences the borrower's investment decision. Herding effects and/or the last minute panic or 'race-in' effect, prevail even without direct communication between the individuals in the crowd. As mentioned in the EduPlayBox case, CrowdEquity suggests sparking herding effects directly at funding begin by making acquaintances invest, because as soon as the funding drive stagnates it directly decreases investor trust as seen in the case of FeedApp. Further, economic, social, political or cultural trends can influence campaigns; for example, EduPlayBox investors mention their interest in investing into the trending education field.

Opinion Leaders: the opinions of experts, gatekeepers and other trusted and well-known individuals influence investors, i.e. when a famous German business angel invested in FeedApp. Other examples were mentioned by a crowdfunding expert (FX): *"[You need] multipliers, advocates – famous people from the crowdfunding scene like [the founder from*

SimpleServ] or someone like Rene Obermann who was still chairman [of the Deutsche Telekom] during our funding, to say 'I believe in [name of the startup]'. [...] this has an immense effect".

The platform: CrowdEquity influences the funding drive in several ways, i.e. by creating artificial shortages, via the rank in the investment list; the pre-selection of startups and the number of projects online at the same time, impact the availability of capital for each project. With regard to CrowdEquity, CE_E1 states *"we want to stay neutral and give everyone the same chance [...], which is difficult regarding the advertisement",* i.e. communication by the platform influences investors. CrowdEquity tries to position itself as transparently as possible (CE_E1; CE_E3).

Unpredictable conditions: unforeseeable events can directly impact the decision-making process of investors, i.e. the technical problem during the second CrowdEquity funding of FeedApp, or the NSA affair, which probably influenced the second crowdfunding of SimpleServ.

The media: we found some evidence that investors, who heard of a particular startup before seeing the project on CrowdEquity, were more willing to invest (I1). The media have a direct impact on investor's decisions by driving awareness, which explains why many founders and CrowdEquity employees outline the importance of PR. This was also shown in the SimpleServ case.

3.8.4 Trust

Considering the findings of the case studies and the literature, especially the Commitment-Trust Theory (Morgan and Hunt, 1994), trust builds a core element of our model. However, the theory does not fit to the relation between an investor and a startup because the information asymmetries in crowdfunding are not balanced as in an equal partnership (see Kortleben and Vollmar, 2012; Schwienbacher and Larralde, 2012). The Crowd Investor Decision Model is therefore based on the viewpoint of the principal (the investor). However, some of the elements of Morgan and Hunt's model (1994) were observed in crowdfunding. The investor's trust in a startup is influenced by the 'shared values' and 'opportunistic behavior' of the precursors. Another factor we identified is "perceived reputation", referring to existing findings (e.g., Corritore et al., 2003; Ganesan and Hess, 1997). Corritore et al. (2003) see reputation as a sub-dimension of credibility, as well as honesty, expertise and predictability. As seen in the cases, personality and expertise of the founders and team also play important roles in trust-building. Next, we associate predictability with 'opportunistic behavior' as we argue that a startup whose actions are predictable and transparent will decrease the risk of opportunistic behavior (cf. Kortleben and Vollmar, 2012). Finally, the business idea with the investor's subjective preference leads to either trust or mistrust regarding success. The four precursors of trust in the Crowd Investor Decision Model are further detailed below.

<u>Personality, Expertise and Shared Values:</u> trust can be built when both parties in a relationship share the same values, aim to reach the same goals and reach agreement on what is appropriate or inappropriate (Morgan and Hunt, 1994). The importance of shared values is illustrated by the following quote*: "[About a social startup:] I participated in the investor call but it did not appeal to me. It was too idealistic, not realistic enough. I am a bit unemotional at this point - for me it depends on the return rather than improving the world!"* (I2). Thus, when identification with the startup's values is lacking, investors may decide against investing. Further, personal traits of the team can build investor trust – charisma, honesty and the appearance of the founders are explicitly mentioned in the interviews. Moreover, investors look for expertise and experience in the given market, which, we find, plays a crucial role in their decision-making process. Investors often look for a combination of different personalities and backgrounds (I4, I2; CE_E2). These decisions in crowdfunding are often made on a subjective

and affective level, which can be seen by the following comment: *"Having no trust in a team […] is a gut feeling […], no hard criteria which can be applied"* (I4). The investor (I4) outlines that it is also much more difficult to get an impression of the founders' personalities online.

<u>Perceived Reputation</u> of the firm plays a strong role regarding trust-building and is formed by communication and the external environment. The relationship of the investor to different external factors and their subjective importance determines how strong and in which direction communication influences him. The crowd signals reputation through herding, opinion leaders through their recommendations, or the media by reporting on the startup. The platform also plays an important role: due to CrowdEquity's pre-selection of startups, the firms already have a positive reputation before beginning their funding period. Investors trust CrowdEquity and therefore also their selection (FA_E1; I4). These external influences together form the perceived reputation, which either increases or decreases the level of trust.

<u>Predictability and Opportunistic Behavior:</u> opportunistic behavior correlates negatively with trust (Morgan and Hunt, 1994). The principal-agent model of Kortleben and Vollmar (2012) underlines the danger of opportunistic behavior. In the interviews one of the founders says (EB_F1): *"Crowdfunding gives founders a lot of freedom but freedom can always be misused by founders, who could use the money for whatever they want"*. CrowdEquity protects the crowd from fraud, but the Kickstarter crowd in the US was already confronted with several fraud cases (Nunez, 2014). To overcome this perceived danger of free-riding, Kortleben and Vollmar (2012) recommend transparency and open communication which make the startup's actions more predictable.

<u>Business Idea:</u> our findings indicate that the startup's idea significantly influences the investor's trust. According to CrowdEquity, investors seek innovative ideas and game-changers (CE_E1; CE_E2). I1 reports that he is attracted by technical vision.

3.8.5 Risk

Investment decisions are not based on trust alone: "*[about not investing in FeedApp] That had nothing to do with their communication [...] or that no trust was given - it was a number based decision for me*" (I4). Our findings show that, comparable to relations in the banking sector (cf. Humphrey and Schmitz, 1998; Mukherjee and Nath, 2003), perceived investment risk plays an important role in crowdfunding. While trust is more dependent on emotional factors, perceived risk is instead presumed to be based on rational elements. The cases show that an experienced team increases trust in the team and idea, which in turn decreases perceived risk (I1;I2;I4;CE_E2). The factors influencing perceived risk are described in the following.

<u>Business model and scalability:</u> the subjective assessment of the business model seems to strongly influence perceived risk. This is shown in the case of EduPlayBox, where investors are attracted by the clear explanation of how they earn money. On CrowdEquity, it became apparent that some investors did not invest in specific startups because they did not believe in the business models (I2; I4). Scalability is also mentioned as relevant (I4, CE_E1). Startups, which can already show revenues, reduce perceived risk, which in turn strengthens trust (CE_E3).

<u>Market</u>: one of the employees of CrowdEquity (CE_E2) remarks about SofaSurf: "*The crowd decided quite well and said 'Perhaps there is no market opportunity or the market is already fully developed' [...] explaining the reluctance of the crowd*". If the investors get the feeling that there is no market opportunity, then the perceived risk is high, which results in a lack of trust: "*One main challenge of building trust is achieving high revenues and a proof of market. It is the best thing you can have because then you know that the idea is working and you don't have this uncertainty as an investor anymore*" (CE_E3). An interviewee from CrowdEquity

adds: "*Lately proof [of basic assumptions] matters more to investors. Maybe because we are placing more startups which are further developed*".

USP and differentiation: *"Clearly differentiating from the competition and a strong USP pull the crowd – the most important aspect"* (CE_E1) – this quote underlines the importance of the USP and differentiation of the startup in the investor's decision. SofaSurf, a for-profit copycat of Couchsurfing and the only project on CrowdEquity that did not pass the funding threshold, according to CE_E1, positioned itself between two large players in the market which did not clarify to investors why a third approach was needed. Interestingly, copycats often prove unsuccessful in crowdfunding, because the risk arising from competition is perceived to be too high (CE_E1). This might be a subjective attitude of crowd investors since follower strategies have also proven to be very successful (Shankar et al., 1998).

All the sub-elements of trust and perceived risk can be influenced by the macro elements. An opinion leader's concrete comment about a business model does not necessarily influence the startup's overall reputation but may increase or decrease perceived risk.

3.8.6 The Investment Deal

A third factor, the investment deal, influences the final decision. The first part of the deal is the valuation. Startups in a very early phase usually offer a much lower self-valuation to crowd investors than those that already have some market-based proof. On CrowdEquity valuation is done by startups themselves in consultation with the platform. In the case of SofaSurf, CE_E1 believed that the valuation was too high, i.e. the risk and trust levels did not justify the high valuation. One investor (I4) remarked: *"The valuation is very important for me. Especially on CrowdEquity there have been a few cases where I found projects really attractive but the valuation was exaggerated and so I didn't join."* One startup he considered overvalued was SimpleServ, for which he saw too high a risk to position in the hardware market. Other investors also outlined the importance of the valuation for their decision (I2; I3).

In the case of CrowdEquity, the goody is part of the investment deal. As seen with SimpleServ and EduPlayBox, goodies can strongly influence the investor's decision, especially regarding investment size. For example, a crowd-funded startup offered a purchase option for the first helicopters produced to investors who offer € 10.000. According to CE_E3 this strongly influenced the investors' decisions, resulting in an average investment amount of € 1.598, very high on CrowdEquity.

Finally, communication is an effective way for startups to impact both the micro and macro levels. On CrowdEquity, for example, the project page and video, investment story and business plan influence how the startup is perceived. This presentation can influence every sub-element of trust and perceived risk e.g. make the team and the idea tangible, their intentions transparent, explain the market, outline the USP, or underline the advantages of the business model. In the macro environment, opinion leaders, the platform, and the media may be particularly influenced by the project page. Further, answering critical questions and communicating openly with the crowd lead to success in funding, as indicated both in the cases and theory (Larrimore et al., 2011). A startup team must possess the skills to communicate with the crowd: openness, honesty, promptness and regularity are essential (CE_E1; CE_E2; CE_E3; I4). The ability to emotionalize is necessary, as seen with SimpleServ, because most crowd investors are not as rational as traditional investors (EB_F3; FX). However, rational investors should also be addressed, which was done effectively by EduPlayBox through their business model calculations.

3.9 Implications for practice

This paper provides deeper insights into the decision-making of crowd investors, which often clearly departs from pure rationality and comprise affect and social or experiential trust as decision components. Startups should understand how to reduce perceived risk, how to build trust and which benefits convince the crowd. Our findings can enable platform providers and future startups to better understand how to approach investors in the crowd. For example, a startup without an experienced team can derive from the model that this may lead to a lack of trust, which then needs to be compensated, i.e. by a good PR strategy, which influences the media or convinces opinion leaders. We have gathered some recommendations for founders from our results in Table 4 below.

Table 4 Overview of the Recommendations for Founders

ACTION	DESCRIPTION
Timing	Founders should not start their campaign while another successful and large campaign is running on the chosen crowdfunding platform.
Communication	Founders should try to build up a large number of early investors to leverage herding effects. This can be done through personal networks but also social media and PR strategies.
	Constantly updating investors and potential investors about the progress will support to convince more follower investors and will also encourage existing investors to increase their initial investment.
	A great and convincing storyline around the team and the product will help to support creating a buzz.
Presentation	The presentation of the idea, business model, and team should be presented in an authentic and easily comprehensible style. Providing a video with the most important insights at the beginning has shown to be most effective. Not being overly optimistic also seems to be a good recommendation, especially if a second round of crowdfunding might be needed and expectations have to be managed.
B2C Products or Services	Easy to understand products that are targeted towards end consumers and the mass market are much more likely to receive a large sum via crowdfunding. B2B products should be presented in a way that end consumers can also easily understand their value and application.
Testimonials	Well known and reputable testimonials will tremendously increase trust of crowd investors in project.
Limitations	Limitations have shown to be very effective. Initially setting a lower funding goal, which closes funding when it is reached, will foster investors to invest more quickly. The funding goal can then be increased stepwise.
Goodies	Offering goodies such as an investor's dinner or one of the first products on the market can largely increase the average funding, especially when combined with a threshold amount that must be given to receive the specific goody.

3.10 Limitations and Further Research

This study has several limitations. First, our sole focus on the CrowdEquity platform implies that our model might not generalize to other types of crowdfunding, such as donation-based crowdfunding. In donation-based settings, the warm glow from giving is likely to play a significant role and the presence of additional donating parties may lead to crowding out (Andreoni, 1990). Corroborating the Crowd Investor Decision Influence Model with other equity or lending-based crowdfunding platforms as well as donation and reward-based concepts could reveal findings about the role of the platform itself in the decision-making process. The evidence for the model could also be strengthened by quantitative research, testing for interdependencies between the identified components. Moreover, it would be interesting to investigate the relative importance of trust for affective decision-makers on the one hand and the roles that perceived risk and knowledge of benefits play for rational decision-makers on the other. Here a more fine-grained look at trust (and distrust), as discussed in the theory section, could be enlightening.

3.11 References (Second empirical study)

Ahlers, G. K., Cumming, D., Günther, C., & Schweizer, D. (2015). Signaling in equity crowdfunding. *Entrepreneurship Theory and Practice*, *39*(4), 955-980.

Agrawal, A., Catalini, C., & Goldfarb, A. (2014). Some simple economics of crowdfunding. *Innovation Policy and the Economy*, *14*(1), 63-97.

Akerlof, G. A., & Shiller, R. J. (2010). *Animal spirits: How human psychology drives the economy, and why it matters for global capitalism*. Princeton University Press.

Andreoni, J. (1990). Impure altruism and donations to public goods: A theory of warm-glow giving. *The economic journal*, *100*(401), 464-477.

Bailey, J. P. (1998). *Intermediation and electronic markets: Aggregation and pricing in Internet commerce* (Doctoral dissertation, Massachusetts Institute of Technology).

Belleflamme, P., Lambert, T., & Schwienbacher, A. (2014). Crowdfunding: Tapping the right crowd. *Journal of business venturing*, *29*(5), 585-609.

Ben-Ner, A., & Putterman, L. (2009). Trust, communication and contracts: An experiment. *Journal of Economic Behavior & Organization, 70*(1), 106-121.

Brabham, D. C. (2008). Crowdsourcing as a model for problem solving: An introduction and cases. *Convergence*, *14*(1), 75-90.

Brunnermeier, M. K. (2001). *Asset pricing under asymmetric information: Bubbles, crashes, technical analysis, and herding*. Oxford University Press on Demand.

Buller, D. B., & Burgoon, J. K. (1996). Interpersonal

Camille, N., Tsuchida, A., & Fellows, L. K. (2011). Double dissociation of stimulus-value and action-value learning in humans with orbitofrontal or anterior cingulate cortex damage. *Journal of Neuroscience*, *31*(42), 15048-15052.

Chang, S. J. (2004). Venture capital financing, strategic alliances, and the initial public offerings of Internet startups. *Journal of Business Venturing*, *19*(5), 721-741.

Coleman, J. S. (1990). Relations of trust. *Foundations of Social Theory, Cambridge, London*, 91-116.

Costa, A. C. (2003). Work team trust and effectiveness. *Personnel Review, 32*(5), 605-622.

De Bettignies, J. E., & Brander, J. A. (2007). Financing entrepreneurship: Bank finance versus venture capital. *Journal of Business Venturing*, *22*(6), 808-832.

Devenow, A., & Welch, I. (1996). Rational herding in financial economics. *European Economic Review*, *40*(3), 603-615.

Fairlie, R., Robb, A., & Robinson, D. T. (2015). Black and white: Access to capital among minority-owned startups.

Flanigan, S. T. (2017). Crowdfunding and Diaspora Philanthropy: An Integration of the Literature and Major Concepts. *VOLUNTAS: International Journal of Voluntary and Nonprofit Organizations*, *28*(2), 492-509.

Furlong, D. (1996). The Conceptualization of 'Trust' in Economic Thought.

Gerber, E. M., & Hui, J. (2013). Crowdfunding: Motivations and deterrents for participation. *ACM Transactions on Computer-Human Interaction (TOCHI)*, *20*(6), 34.

Gompers, P. A., & Lerner, J. (2002). The money of invention. *Ubiquity*, *2*(43), 1.

Helms, B. (2006). Access for all: building inclusive financial systems. *Washington, DC, C-GAP*.

Hemer, J. (2011). *Crowdfunding und andere Formen informeller Mikrofinanzierung in der Projekt-und Innovationsfinanzierung*. Fraunhofer Verlag.

Herzenstein, M., Sonenshein, S., & Dholakia, U. M. (2011). Tell me a good story and I may lend you money: the role of narratives in peer-to-peer lending decisions. *Journal of Marketing Research*, *48*(SPL), S138-S149.

Howe, J. (2006). The rise of crowdsourcing. *Wired magazine*, *14*(6), 1-4.

Kleemann, F., Voß, G. G., & Rieder, K. (2008). Un (der) paid innovators: The commercial utilization of consumer work through crowdsourcing. *Science, technology & innovation studies*, *4*(1), PP-5.

Knack, S., & Keefer, P. (1997). Does social capital have an economic payoff? A cross-country investigation. *The Quarterly journal of economics*, *112*(4), 1251-1288.

Kromidha, E. (2015, November). A comparative analysis of online crowdfunding platforms in USA, Europe and Asia. In *eChallenges e-2015 Conference, 2015* (pp. 1-6). IEEE.

Kuppuswamy, V., & Bayus, B. L. (2015). Crowdfunding creative ideas: The dynamics of project backers in Kickstarter. SSRN Working Paper.

Kuwabara, K., Willer, R., Macy, M. W., Mashima, R., Terai, S., & Yamagishi, T. (2007). Culture, identity, and structure in social exchange: A web-based trust experiment in t the United States and Japan. *Social Psychology Quarterly*, *70*(4), 461-479.

Lambert, T., & Schwienbacher, A. (2010). An empirical analysis of crowdfunding. *Social Science Research Network*, *1578175*, 1-23.

Lehner, O. M. (2013). Crowdfunding social ventures: a model and research agenda. *Venture Capital*, *15*(4), 289-311.

Lukkarinen, A., Teich, J. E., Wallenius, H., & Wallenius, J. (2016). Success drivers of online equity crowdfunding campaigns. *Decision Support Systems*, *87*, 26-38.

Meer, J. (2014). Effects of the price of charitable giving: Evidence from an online crowdfunding platform. *Journal of Economic Behavior & Organization*, *103*, 113-124.

Miles, M. B., & Huberman, A. M. (1994). *Qualitative data analysis: An expanded sourcebook*. sage.

Mollick, E. (2014). The dynamics of crowdfunding: An exploratory study. *Journal of business venturing*, *29*(1), 1-16.

Pennebaker, J. W., Booth, R. J., & Francis, M. E. (2007). Linguistic inquiry and word count: LIWC [Computer software]. *Austin, TX: liwc. net.*

Porta, R. L., Lopez-De-Silane, F., Shleifer, A., & Vishny, R. W. (1996). *Trust in large organizations* (w5864). Retrieved from http://scholar.harvard.edu/files/shleifer/files/trust.pdf

Sen, R., & King, R. C. (2003). Revisit the Debate on Intermediation, Disintermediation and Reintermediation due to E-commerce. *Electronic Markets*, *13*(2), 153-162.

Spulber, D. F. (2010). Solving the circular conundrum: communication and coordination in internet markets. *Nw. UL Rev.*, *104*, 537.

Sonenshein, S., Herzenstein, M., & Dholakia, U. M. (2011). How accounts shape lending decisions through fostering perceived trustworthiness. *Organizational Behavior and Human Decision Processes*, *115*(1), 69-84.

Stein, J. C. (2002). Information production and capital allocation: Decentralized versus hierarchical firms. *The journal of finance*, *57*(5), 1891-1921.

Teece, D. J. (1998). Capturing value from knowledge assets: The new economy, markets for know-how, and intangible assets. *California management review*, *40*(3), 55-79.

Venkataraman, S. (1997). The distinctive domain of entrepreneurship research. *Advances in entrepreneurship, firm emergence and growth*, *3*(1), 119-138.

Vulkan, N., Åstebro, T., & Sierra, M. F. (2016). Equity crowdfunding: A new phenomena. *Journal of Business Venturing Insights*, *5*, 37-49.

Weidenbaum, M. L., & Hughes, S. (1996). *The bamboo network: How expatriate Chinese entrepreneurs are creating a new economic superpower in Asia*. Simon and Schuster.

Wiltbank, R., & Boeker, W. (2007). Returns to angel investors in groups. Ewing Marion Kauffman Foundation & Angel Capital Education Foundation. Available via SSRN.

Yamagishi, T., & Yamagishi, M. (1994). Trust and commitment in the United States and Japan. *Motivation and emotion*, *18*(2), 129-166.

Yuki, M. (2003). Intergroup comparison versus intragroup relationships: A cross-cultural examination of social identity theory in North American and East Asian cultural contexts. *Social Psychology Quarterly*, 166-183.

Yuki, M., Maddux, W. W., Brewer, M. B., & Takemura, K. (2005). Cross-cultural differences in relationship-and group-based trust. *Personality and Social Psychology Bulletin*, *31*(1), 48-62.

Yunus, M. (2007). *Banker to the Poor*. Penguin Books India.

Yunus, M., Moingeon, B., & Lehmann-Ortega, L. (2010). Building social business models: Lessons from the Grameen experience. *Long range planning*, *43*(2), 308-325.

Zheng, H., Li, D., Wu, J., & Xu, Y. (2014). The role of multidimensional social capital in crowdfunding: A comparative study in China and US. *Information & Management*, *51*(4), 488-496.

3.12 Appendix: Guiding Questions - Summary

The guiding questions below were translated from German by a dual native speaker.

3.12.1 Questions - CrowdEquity

3.12.1.1 General questions about the platform

- How strongly were the ideas and business models tested on your side before you put them on the platform?
- What additional information do investors receive on top of what is available in the restricted section of the homepage?
- On the website it states that your task is to attract new investors - what are your concrete steps in this direction?
- To what extent can you boost your funding through marketing and PR? Which channels are the most important for you?
- Which elements on the website support the start-ups to gather funding (from the crowd)?
- Question on the investment opportunities list of the site: If several projects start simultaneously (or during overlapping timeframes) and one is quickly pushed out the top rank of the list - do they have a harder time? Do you have experience values?

Goal: to clarify remaining ambiguities, to capture the influence of the CrowdEquity team and platform

3.12.1.2 Factors influencing success

- What does CrowdEquity recommend for founders to succeed?
- Which recommendations do you personally have for founders to succeed?
- Which elements on the platform help to increase funding for individual projects?

• How is the investment opportunity list generated? How is prioritized? Does the same prioritization apply in the overview area?

• To what extent can you boost your funding through marketing and PR? Which channels are the most important for you?

• How is the project length defined? What influence does the project length have on (funding) success?

Objective: To identify success factors, to inquire details about success-influencing elements

3.12.1.3 Crisis Management

• What kind of actions do you take when the funding process for a start-up is going rather slowly?

• What recommendations do you make to the startups in such a situation?

Goal: What factors have short-term and strong effects on the funding process? How can one quickly attract investors?

3.12.1.4 Funding process and group effects

• At which points during the funding process are challenges more likely, at which points less likely?

• For what reasons do start-ups (on the platform) have the possibility to increase their funding limit afterwards?

• What is the effect of an increase in the funding limit on the funding process?

• To what extent do (CrowdEquity) investors interact?

• How did the project team in particular jump-start the funding process at the beginning?

• How could you help with this process?

• What can be done when the funding process is cumbersome?

Goal: Are group effects in crowdfunding? What are the main hurdles for the start-ups?

3.12.1.5 Investor Motivations

• Can you tell us about your investors?

• Who is the typical CrowdEquity investor?

• What motivates your investors to invest?

• Did you receive negative feedback from investors when a project failed and investors lost money? How do you deal with this?

• What is the difference between a Crowdfunder and a traditional investor?

• Based on which criteria do your investors make their decisions?

• Are there cases where investors closely cooperate with start-ups (on CrowdEquity)?

Goal: Which criteria do crowd investors use when making investment decisions? What motivates investors (in this setting)?

3.12.1.6 Prestige Projects

• Which projects do you consider your 'prestige projects'?

• For what reasons was the project particularly successful?

• Which project has been particularly successful recently?

• For which reasons?

• Can you remember what the founders of X did on the first day to drive fundraising (i.e. to kickstart the funding process)?

• What is particularly important in terms of the startup’s communication with investors?

Goal: Which projects were particularly successful and for which reasons? To identify potential interview partners

3.12.1.7 Failed Projects

- Are there any projects on CrowdEquity that have not received funding?
- In your opinion, what are the reasons why project (x) did not reach the funding threshold?
- Are there any projects where the funding process progressed only slowly?
- What did the founders do wrong in this case so that funding did not start or progress well?
- Which factors determine success on CrowdEquity?
- What things do startups frequently not execute very well (on CrowdEquity)?

Goal: The identification of: What mistakes were made? What could be learned from the project?

3.12.2 Questions - Startups

- When and why did you choose Crowdfunding (as a funding option)?
- How much preparation time was required?
- What had to be done during the preparatory period?
- How did you prepare for the funding?
- What did you focus on when you presented XY at CrowdEquity? (Video / story / business plan)?
- How did you produce the video?
- How was it on the day that the funding process began?
- How has it been during the course of the (entire) process?
- How did you react to the funding development?
- Are you satisfied with the result that you achieved?
- What was a very special learning for you in the investor search via Seed-match?
- What went very well in the process, what went less well?

• What is important when Crowdfunding a startup? What do you need to pay particular attention to?

• How could your Goody help lure additional investors?

• How did the crowdfunding process affect your team?

• Why did XY choose Crowdfunding? What were the advantages and disadvantages?

• What is the image of CF today in the financing sector?

• How did you get the crowd to invest?

• How did you approach potential investors?

• With which means did you win the most investors? (How many investors did you bring with you to the process yourself? (i.e. out of your own network))

• How deep do 'potential investors from the crowd dig?

• How did you deal with criticism?

• What were your most important communication channels?

• How did you try to attract investors through the video?

• How did you use social media to attract investors?

• How did participation in crowdfunding affect your motivation?

• What were the most important elements of your (startup's) representation on CrowdEquity? (To what extent did the graphical preparation of your content play a role?)

• How did you build up/design the video in oder to be successful?

• Why did you decide to present the funding goal in detail in the video?

• How critical were the questions asked by Crowd investors?

• How was the crowd able to help you over the past year?

• How do you try to use the Crowd as a resource?

• How would you run a crowdfunding campaign today, what would you do differently?

• What led you to choose CrowdEquity?

• How did you benefit from being funded at CrowdEquity?

• How could CrowdEquity support you?

• Were there times when you were particularly dependent on the help of the CrowdEquity team?

• Which channels did you use during the funding process to communicate with the crowd?

• Did you have a moment when communication with the crowd was difficult?

• Do you have a sense of what types of people (investors) are sitting on the other end and have invested in you?

• Were you able to build up close relationships with individual investors via crowdfunding?

• To what extent do you still have contact with the crowd today?

• Why were you successful?

• What did you learn from the crowdfunding process?

• What would you do differently today?

• What advice would you give to a startup that wants to crowdfund?

• What surprised you especially about Crowdfunding on CrowdEquity?

3.12.3 Questions - Investors

• How did you land on CrowdEquity?

• In which companies did you invest? Tollabox, Protonet, Honestly?

• How did you hear about the project?

• When XY showed up on the platform, what did you like about the project pitch?

• When did you decide to invest?

• What convinced you most about XY?

• Why did you invest / what kept you from investing?

• What unanswered questions remained before you invested?

• How did you get into contact with the company (investor channel, investor calls, email, investor relations)?

- How well was startup X reachable for you?
- How did they provide feedback to the company?
- Video / Investment story / Businessplan?
- How did the startup present itself?
- How did you feel about the communication of XYZ? What was especially noticeable?
- How did you experience the first day of funding?
- How did you like the goody (incentive) XY?
- Why was XYZ successful / unsuccessful?
- What do you do/what is your process when you invest in CrowdEquity?
- How did you like the team of XYZ?
- Did you participate in the investor call?
- To what degree do you pay attention to how much is invested by other investors?
- To what extent do you make your (investment) decision dependent on the funding process?
- What is important to you in your decision (to invest or not)?
- What role does trust play in your investment?
- How can the company build confidence (i.e. gain confidence of crowd-investors)?

4. Reaching Agreement on Contribution Behavior – Evidence on Cultural Differences from a Public Goods Game with Representatives in Japan and Germany

Abstract

We discuss the results of an experimental public good game with group representatives in Germany and Japan, countries with varying levels of individualism. Representatives are permitted to communicate with their constituencies, but not with other representatives. We focus on accountability between representative and his constituency and on the risk taken in the interaction between representatives. German and Japanese subjects differ not only in their contribution behavior, but in their ability to reach agreement on strategy in pre-play communication. We find that between-country differences can be explained to a large extent by the framework for group behavior proposed by Yuki (2003).

Keywords: Public Goods, Negotiation, Decision-Making, Communication, Culture, Lab Experiment

JEL Classification: H41, J16, C91

Authors: This paper was written in collaboration with Prof. Dr. Christiane Schwieren and Prof. Dr. Yoshio Iida. With respect to the distribution of work, the following declaration can be made: The basic research idea, as well as the initial conceptual model were developed by Christiane Schwieren and Yoshio Iida. The theory section on trust as well as the statistical analysis and regressions were done by all authors but with the lead of Andrew Isaak.

Project History (extract): Prior versions of this article have been presented at the 6th International ACCER Workshop on “Cross-Cultural Experiments in the Social Sciences, Economics and Management”, Duisburg, Germany, March 6th-7th, 2017, the 2015 Conference on “Consciousness and Intention in Economics and Philosophy”, Kyoto, Japan, December 12th-13th, 2015 and the 7th FINT Workshop on “Trust within and between Organizations”, Singapore Management University, November 21st-23rd, 2013. The article is currently under review at the Journal of Behavioral and Experimental Economics (VHB: B).

Reaching Agreement on Contribution Behavior – Evidence on Cultural Differences from a Public Goods Game with Representatives in Japan and Germany

4.1 Introduction

Tradeoffs between individual and group/societal interests, as exemplified by the case of the provision of public goods, are common subjects of debate across human societies. A fundamental and much studied question across the social and behavioral sciences, is to which degree individuals behave according to their individual interest compared to the interest of the larger group in various settings (i.e. given prevailing norms and local incentive structures). Thus, understanding and identifying causes of group differences is important to explicate the role of culture in economic development. Social identity is commonly defined as a person's sense of self derived from perceived membership in social groups (e.g. Chen and Li, 2009). A stream of literature in social psychology explores social categorization into (perceived) ingroups and outgroups (e.g. Tajfel et al, 1971). Economists are increasingly studying the effect of group membership on preferences (Akerlof and Kranton 2010; Benjamin et al, 2010[44]). Also, due to the discontinuity effect[45], competition and conflict may be better observable when groups rather than individuals interact (e.g. Wildschut & Insko, 2007). Game experiments provide rigorous measurement of group differences in preferences (van Hoorn, 2018). While in-group favoritism is often reported, Pan and Houser (2013), using a modified trust game, find that groups formed around cooperative production did not engage in in-group favoritism or out-group discrimination. Such mixed results call for further studies on out-group bias. In particular,

[44] Benjamin et al. (2010) find that Asian identity can affect time preferences.
[45] The discontinuity effect suggests that interacting groups display more competitiveness than interacting individuals. Social psychologists believe it is due, among other things, to in-group favoritism and diffusion of responsibility (e.g. Pinter et al, 2007; Wildschut & Insko, 2007).

less research has been conducted with a focus on the interests of a small *group* against those of larger societies, which is one contribution of the current paper.

We focus on a specific setting: interactions between representatives of groups. The conflict of interest is between the interest of the group of each of the representatives and the interests of "society" as a whole, in our case comprised by three groups with one representative each (captured by our representative treatments "R1" and "R2", as will be explained in the following sections). The possible personal interest of the representative is not part of our study and not modelled in the experiment. As demonstrated in an earlier paper (Iida & Schwieren, 20015), to risk behaving cooperatively towards other representatives, representatives must know that their constituency[46] (the group they represent) accepts them taking this risk. In the paper (Iida & Schwieren, 2015) it was also shown that, in a Spanish context, representatives' knowledge of whether or not their constituency accepts their (risky) cooperative behavior towards representatives of other groups is indeed important in determining cooperation. Here, we build on this work by studying the additional aspect of intercultural variation along the dimension of individualism, which captures the degree to which an individual's self-image is defined in terms of 'I' or 'we' (Hofstede, 2010; Minkov, 2017). The principle distinction between individualist and collectivist societies "lies in the degree of ingroup identity and loyalty" (Yuki and Takemura, 2014: 39). People in collectivist cultures may subordinate personal goals to collective goals or make no distinction between them (Yuki and Takemura, 2014; Triandis, 1995). Japan is a prototypic example of a collectivist country (Ibid).

Yuki´s (2003) framework for understanding group behavior in collectivist countries (which drawing on Triandis, 1995) leads us to expect differences in relatively "minimal" intergroup situations[47] between individualistic and collectivistic countries (emphasizing the group over the

[46] Constituency is defined by Merriam-Webster Dictionary as „a body of citizens entitled to elect a representative". We use the term more loosely to mean the group someone represents. https://www.merriam-webster.com/dictionary/constituency, as accessed on May 21st, 2018.

[47] In a seminar paper, Tajfel et al. (1971) specified a number of criteria required for a group classification to be 'minimal', including no face-to-face interaction, anonymity of group membership, etc. For details see the paper.

self) in general, but also in the effect of communication between representative and constituency on cooperative behavior of representatives (Yuki, 2003; Yuki and Brewer, 2014). Such differences in ingroup identity and loyalty have been shown to manifest themselves in communication styles, social judgment, etc. (e.g. Fiske et al, 1998; Smith & Bond, 1999).

Our expectation of behavioral differences between subjects from each type of society is further strengthened by the work of Yamagishi (1998, 2011) who finds that in comparison to Japanese respondents, American respondents, from an individualistic country, are more trusting of others in general and consider (individual) reputation to be more important. We therefore compare public good contribution behavior in Germany, a rather individualistic, European country, with Japan, the classical example of a collectivistic country (Hofstede, 2010; Minkov, 2017)[48]. Our research questions concern intercultural differences in negotiations of group representatives that do not know each other and also do not know their constituency very well in the public goods setting. More precisely these are:

(1) How does behavior differ between countries?

(2) How does communication content differ?

The next sections are structured as follows: we first discuss a relevant framework for group behavior and the concept of individualism before developing our hypotheses. This is followed by an explanation of the experimental setup and procedure and presentation and discussion of the results. We conclude the paper with limitations of the study and suggestions for future research.

[48] The two countries differ in other aspects as well, but the most prominent – and for the current research most relevant – difference is in individualism/collectivism.

4.2 Yuki's Model of Group Behavior

The core framework for our research is the model of Yuki, which directly focuses on a comparison between group behavior in Asian und "Western" countries. Yuki and colleagues stress that in Asian collectivist cultures people need to form strong personal relationships in order to be able to trust each other and, therefore, do not cooperate with strangers easily (Yuki, 2003; Yuki, Maddux, Brewer, & Takemura, 2005). Thus, there is a specific word for a network of reciprocal relationships in Chinese, *Guanxi,* without a direct English equivalent[49]. Clearly such relationships rely on experience through interaction (e.g. communication/signalling).

Yuki furthermore stresses that joint category membership is less important (and not sufficient) for building trust in collectivist countries, unlike in individualistic countries (Yuki, 2003; Yuki et al., 2005), thus we expect that we need meaningful groups to get group-favoring behavior (ingroup bias) in collectivistic cultures, while in individualistic cultures "minimal" groups might be sufficient (e.g. Falk, Heine and Takemura, 2014).

Behavioral economic studies of public good behavior, with notable exceptions (Hauge & Rogeberg, 2015; Rode, 2010), typically fail to consider the role of third parties or group representatives. Only one of these two studies deals with group representatives (Hauge & Rogeberg, 2015), but mainly focuses on gender differences [50](the authors find that women make less self-interested choices as group representatives than men, implying the importance of socialization).

[49] There is an equivalent term in Russia – at the intersection between Europe and Asia – termed *Blat*; Thus, in Russia and China, informal relationships are often used to circumvent formal procedures to obtain goods and services, traditionally hard to obtain in centrally planned economies, at least until 1989 (e.g. Ledeneva, 2008).

[50] Also, in the experiment by Hauge and Rogeberg (2015), three subjects were randomly forced to go public by writing their contributions on a flip chart for other subjects. This is a very different mechanism then we use here.

4.3 Cultural Variation in Individualism

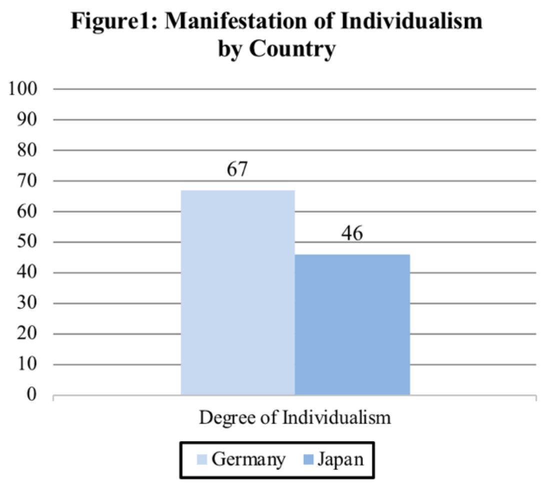


Figure 1: Manifestation of Individualism by Country (Hofstede, 2010)

Highly individualist countries have "a loosely-knit social framework in which individuals are expected to take care of only themselves and their immediate families" as opposed to collectivist countries, which show "a preference for a tightly-knit framework in society in which individuals can expect their relatives or members of a particular ingroup to look after them in exchange for unquestioning loyalty"[51]. Characteristics of a collectivistic society include putting harmony of the group above the expression of individual opinions and people having a strong sense of shame for losing face. Thus, the construct *individualism* measures the degree to which an individual's self-image is defined in terms of 'I' or 'we'.

Japanese and German cultures differ significantly on their degree of individualism, as depicted in Figure 1 (e.g. Hofstede, 2010); thus, on a national level, Germany reaches 67 out of 100, a relatively high value on this dimension, while at 46 Japanese show much lower levels of individualism (a relative difference of over 30%). For a number of reasons, we focus solely on variation in the degree of individualism. First, with respect to the behavior we are interested in, we would not expect any of the other dimensions to play a major role. Second, frameworks by

[51] http://geert-hofstede.com/national-culture.html as accessed on Apr. 27th, 2018.

other cross-cultural researchers, Hall and Trompenaars (Hall & Hall, 1990; Trompenaars & Hampden-Turner, 1998), have independently conceptualized similar individualism constructs, implying both high relevance and a degree of theoretical consensus.

Third, recent empirical replications of individualism-collectivism have good internal reliability and face validity and the individualism dimension has shown to be robust to different operationalizations and settings (Minkov, 2017). These include a recent large study by Minkov (2017) and Merrit's (2000) study of airline pilots worldwide. Further, the updated individualism index in Hofstede's work (2010) is highly correlated with similar measures in the large-scale panel data from the World Values Survey (Minkov & Hofstede, 2010), individualism as captured in the GLOBE study of advanced societies (House, Hanges, Javidan, Dorfman, & Gupta, 2004; Minkov, 2017) and Welzel's (2014) emancipative values index. Fourth, the degree of individualism is a factor that receives support from both comparative studies in social neuroscience (Oyserman & Lee, 2008[52]; Chiao et al., 2009; Harada, Li, & Chiao, 2010) and genetics (Chiao & Blizinsky, 2009). Finally, the individualism/collectivism dimension serves for us as a background concept that helps to describe differences between the countries we study. We do not measure individualism but compare subjects from two countries that have been found to differ in a way that seems to be important for intergroup-behavior (e.g. Yuki, 2003), which is the main focus of our study.

4.4 Theoretical Expectations

Based on the theories discussed and the results from previous closely related work (e.g. Iida & Schwieren, 2015) we form a series of hypotheses regarding our research questions. The first set

[52] In a meta-analysis of individualism priming literature, Oyserman and Lee (2008) find moderate evidence for a relationship between individualism and cognition (or the way we think) and relationality (or the way we relate to others, including social sensitivity, perceived social obligations and perceived support from others). Priming refers to the use of cues with the aim of activating specific mental frames (e.g. norms), leading to subsequent mental processes and/or behavioral outcomes (e.g. Oyserman and Lee, 2008; van Hoorn, 2018).

(H1-H3) denote expectations about contribution behavior and the second set (H4-H6) our expected differences in communication content. We expect that the more individualistic a culture, the easier that trust can be placed in a stranger´s cooperativeness, thus the higher the willingness to contribute to a public good in a relatively anonymous laboratory setting.[53] Further, collectivist subjects are less probable to "cheat" on those with whom they have established a cooperative relationship. We therefore hypothesize that:

H1: Germans will trust a stranger's cooperativeness more readily, such that baseline contributions to the public good will be higher in Germany than in Japan.

H2: Over time, we will observe a significant end-effect[54] (lower average contributions in the last two periods than in the first eight periods) in Germany but less so in Japan.

In more individualistic cultures, by being able to talk to one´s constituency, representatives can obtain "permission" to contribute to the public good. If there is no possibility to discuss a strategy, but some ingroup identity has formed between representative and his constituency, we expect that all will play selfishly for "their" group. In collectivistic cultures, by talking to the constituency, personal ties are developed within this group that will increase favoritism within the group but that will obstruct cooperation with strangers (the outgroup). Therefore, we hypothesize that:

H3: In both countries, contributions in (representative) treatment R1 (where participants stay completely anonymous) will be lower than in (representative) treatment R2.

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[53] However, at the same time, shame aversion is likely to be higher among Japan subjects in treatment R2, where additional feedback/accountability is possible in form of a second chat.

[54] Repeated public-goods games conducted in the lab with US or European subjects typically result in some positive contributions to the public good, contrary to the Nash equilibrium of zero. Over many rounds, the average contribution tends to drop as subjects begin to free-ride, the so-called ‚end-effect', see Andreoni (1988).

H4: In Germany (an individualistic country) but not in Japan, groups will more frequently reach agreement (that a representative may try a cooperative strategy) in treatment R2 (where subjects can discuss strategies within their groups) than in treatment R1, such that mean contributions to the public good will be higher in treatment R2 than in R1.

H5: Since reciprocal relationships take longer to establish in collectivist countries, Japanese subjects will not contribute more to the public good when allowed to chat with their constituency for a limited time (in treatment R1 and especially in treatment R2) than in the baseline (without chat).

H6: Groups from collectivist societies tend to need more time to build a relationship with their constituency than groups from individualistic societies, such that German groups will be more able to (more frequently) discuss a strategy (within a limited timeframe) than Japanese groups.

4.5 Experimental Setup[55]

We used a standard public good game as the basic tool for our experiment, as in a previous paper on the topic (Iida & Schwieren, 2015). Based on our research questions, we used one baseline treatment and various "representative" treatments that differed in terms of the informational structure and the number of interactions between the subjects of a given group. The baseline treatment is a simple three-person public good game of ten periods (the groups are fixed throughout the rounds). Subjects have five tokens in each period that they can

[55] The experimental set-up is essentially the same as in Iida & Schwieren (2015), with some exceptions especially in the German group, where we eliminated all "unnecessary" aspects of the design with respect to our main research question, intercultural differences in negotiations of representatives that do not know each other and also do not know their constituency very well. The Japanese dataset comprising the majority our data, hast not been previously reported.

distribute between a personal and a public account. One token in the personal account pays one token for oneself, while one token in the public account pays 0.75 tokens for each subject playing, including oneself. The payoff to individual *i*, U_i, is derived from the following function

$$U_i = (E_i - g_i) + 0.75\sum_{i=1}^{3} g_i \qquad (1)$$

where E_i is the initial endowment and g_i is a voluntary contribution to the group project and 0.75 is the MPCR[56] (e.g. Isaac, Walker and Williams, 1994). The dominant strategy of such a game is to contribute nothing to the public good (i.e. to free-ride) even though the subjects would be best off if everybody contributed all of their tokens to the public good.

The subjects received feedback after each round on the total contribution of the other team members, but not on the individual contributions of each member of their group. The same basic game was used in all treatments; The representative treatments differed in one main respect from the baseline treatment: representatives of three-person teams played the game. Therefore, as illustrated in Figure 2, we have three groups of three people, each involved in one public good game, but out of each group, only one person (the representative) is playing the public good game.

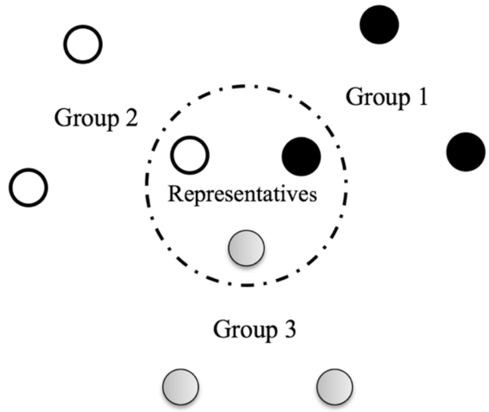


Figure 2: Representative Treatments (1 Unit = 3x3 Subjects)

[56] Marginal per capita return to the public good; a higher factor typically leads to higher contributions.

Contributions to the public good have an effect on all nine subjects within one game. Earnings made by the representatives are equally distributed among all of the subjects of one group, both those playing (the representatives) and those not playing. This is known to subjects in advance of the game. This means that individual earnings are held constant with respect to our baseline-treatment, while "society-wide" earnings are bigger in the representative treatments than in baseline.

In all of the representative treatments, the three-person teams were allowed to talk to each other for five minutes using a chat program before the public good game began. The representative treatments differed with respect to the information available for the chat as well as with respect to repeated chat possibilities and knowledge thereof. For the intercultural comparison we use two different representative treatments that have been played in a similar way in Japan and in Germany[57]. They differ in the following ways from each other:

In treatment R1, subjects were allowed to chat for five minutes with their ingroup before reading the instructions for the public good game. This chat served the only function to enhance their identification with their ingroup and increase the salience of being a group representative for them.[58]

In treatment R2, the subjects received the public good game instructions before chatting for five minutes with their ingroup members. The subjects were instructed to discuss their strategies during the chat time. After the first 10 rounds of the game, they received a second chance to chat with their ingroup members. We introduced the second chat to enhance accountability and give them the chance to justify their actions in front of their group members.

[57] In Iida & Schwieren (2015) another treatment is used that is in-between our R1 and R2 here: Subjects do have a second chat, but do not know about it beforehand. Results for this treatment (run only in Spain) lie in-between results for R1 and R2 described here.

[58] This aspect of our design was inspired by previous experiments that have demonstrated that the salience of group membership can be enhanced by communication (e.g. Charness, Rigotti and Rustichini, 2007; Chen and Li, 2009). Chen and Li (2009) report that in their experiment, participants matched with an ingroup member show a 47 percent increase in charity concerns and a 93 percent decrease in envy. Further, van Hoorn argues convincingly, that identity primes can be used to strengthen the inferential power of experiments (van Hoorn, 2018).

In Japan, but not in Germany[59], we ran an additional 10 periods after this chat unknown to the subjects before. Therefore, we report on the first 10 periods here, which were not affected by the fact that they were followed by 10 more periods in Japan, as subjects learned about them only at the start of these 10 periods.

4.6 Procedure

The experimental sessions were conducted at labs of two universities of similar size and rank in Southern Germany and Western Japan. Due to subject availability and laboratory size our two national groups differ in sample size. We have 87 subjects in Germany and 144 subjects in Japan (n=231). In Germany, 15 subjects were in the Baseline treatment and 36 in each of the representative treatments. In Japan, 27 subjects participated in the baseline, 45 in R1 and 72 in the R2 treatment. Student subjects with various academic backgrounds were recruited via ORSEE (Greiner, 2015), in both cases[60].

Table 3: Summary of Treatments

	Subjects						
Treatment	Germany	Japan	Total	"Active" Decision Makers	Sessions	Female Share	Mean Age
Baseline	15	27	42	42	2	0,39	23,11
R1 Treatment	36	45	81	27	4	0,32	22,95
R2 Treatment	36	72	108	36	4	0,4	22,11
Total	87	144	231	105	10	0,37	22,72

In the representative treatments (R1 & R2) "active" decision makers are the group representatives who decide how much to contribute for their group based on the in-group chat. Therefore, 54 subjects in R1 and 72 subjects in R2 completed calculation tasks in the remaining time.

The experiment was programmed and conducted with the experimental economics software z-Tree (Fischbacher, 2007). Instructions were provided in Japanese in Japan and in

[59] This is certainly not the optimal way of designing an experiment, but it should not affect our results, as Japanese subjects were not aware during the first ten rounds that there would be additional rounds. Due to the temporal ordering and surprise, we therefore believe this difference is unimportant for this paper. Contribution results on the second set of 10 periods in Japan and the underlying raw data can be provided upon request.
[60] As our hypotheses are not about gender or age, we do not discuss this further here. More detail on these can be provided in the online supplemental material or on request.

German for Germany. Translation was conducted by dual native speakers experienced with translation and a pre-test was conducted to validate comprehension of the experiment and instructions. An experimental session lasted about one hour on average and subjects earned an average of €12 (including a €4 show-up fee; payment in Japan was in Japanese Yen, with average earnings of approximately 2000 ¥ per hour[61]). Payments were made privately and in cash. When the subjects arrived at the laboratory, they were randomly seated at computers that were separated by partitions so that they could not see the experimenters, each other or each other's screen. The subjects were organized randomly into non-overlapping three-person groups (using Z-Tree's *random()* function) and, in the representative treatments, into larger nine-person entities comprising three such groups to play the public good game together.

Depending on the treatment, the small groups were first allowed to chat for five minutes about everything except individually identifying information (R1) or they first received instructions for the public good game (R2), which were also read out aloud[62], before chatting. In treatment R2 the groups were asked to chat for 5 minutes about the strategy to follow after reading the instructions – before knowing who would be the representative. Subjects in the baseline treatment were not allowed to chat, but immediately received instructions for the public good game.

After reading the instructions, subjects took a brief test at their computer terminals to verify that they correctly understood the rules (Bigoni & Dragone, 2012). The experiment did not start until all of the subjects had answered the questions correctly. After this training procedure, in the representative treatments, the computer selected a representative for each group at random. Subjects did not know who would be the representative at the time of their ingroup chat.

[61] The average exchange rate at the time was 0,0061 €/¥. Earnings are comparable to that of Pan & Houser (2013), where subjects earned about $15 per session (of similar length).
[62] Instructions were read aloud for three reasons: First it ensures exposure to the instructions. Second it creates common knowledge, needed to test economic theories – everyone knows that everyone knows. Third, this reduces suspicions of deception by reassuring subjects that everyone received the same instructions. (Croson, 2005: 141).

In all of the treatments, the subjects played 10 rounds of the public good game described above. In the baseline treatment, the experiment ended when the public goods game was finished and subjects were privately paid a show-up fee plus their earnings from the experiment. In R2, groups where allowed after the 10 periods to chat again for 5 minutes, to increase feelings of accountability. In the representative treatments, the experiment continued for an additional round in Japan, but this came as a surprise to participants, so it cannot have affected behavior in the first 10 periods. We did this with the idea of obtaining data on further developments, but decided not to repeat it in Germany and not to analyse it in Japan, as we could not reach the sample size necessary for meaningful analyses in both countries. Figure 3 summarizes the baseline and representative treatments.

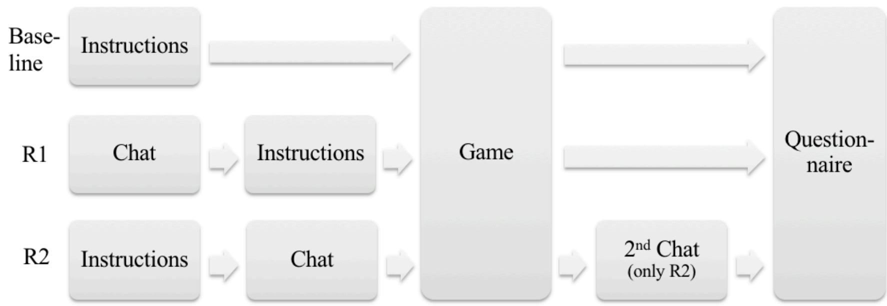


Figure 3: Overview of Baseline and Representative Treatments

At the very end, representatives completed exploratory questionnaires[63]. Then subjects were paid and dismissed. The second chat served only to increase feelings of accountability during the contribution rounds – subjects knew that they would talk to their group members again and thus would most probably feel accountable to them.

4.7 Results

In the following section, we report our results both for contribution behavior and for the chat.

[63] We do not report the questionnaire data as they were only collected for exploratory reasons to inform future research and differed between the countries. As they were collected after the experiment, they cannot have influenced behavior.

To validate our hypotheses, we analyze differences in contribution levels using a combination of parametric and non-parametric test procedures. To increase the validity of our study, we also provide additional tests of within-country differences in the Appendix which further support our hypotheses. Table 2 below depicts mean contributions over all periods of the public good game for Germany and Japan.

Table 4: Germany and Japan, Mean Contributions over all Periods (Std. Dev.)

Treatment	Mean: Germany	Mean: Japan
Baseline	2,820	2,164
	(2,171)	(1,763)
R1	2,450	2,167
	(1,855)	(1,968)
R2	3,517	2,308
	(2,021)	(1,933)

Hypotheses 1&2: Germany and Japan

Since we have two independent samples, we use the Mann-Whitney rank-sum test to compare contribution levels between countries in the baseline-treatment and find that contributions are higher in Germany than in Japan (p=.002, z=3.086). The same holds for both representative-treatments, but while the R2 treatments differ significantly (p<.001, z=5.565), differences for the R1 treatment are not significant (p=.166, z=1.386). Since contributions differ in variance especially between German and Japanese subjects, we repeated the tests with the more conservative Robust Rank-Order Test, which relaxes the assumption of equal variances, (i.e., the underlying distributions may be different when testing equality of medians) with similar results (Baseline: p=.005, U=2.76; R1: p=.174, U=1.360; R2: p<.001; U=5.413). Thus, our results support H1 that German subjects will contribute more in the baseline treatment.

Using a simple eyeball examination, Figures 4 – 5 (see next page) show an end effect for Germany, but nor for Japan, lending descriptive support for H2. Our contribution data showed no signs of heteroskedasticity using the Breusch-Pagen test and variance inflation was not an issue with our data. Further, we tested the normality assumption using the Shapiro-Wilk test, which showed that at least some treatments were normally distributed (particularly the German Baseline and the Japanese R1 treatments). Therefore, below we use linear regression to formally test the significance of the decline in contributions (y) over time (t) over periods 1-10 for each country and treatment group, respectively.[64]

Table 5: Significance of Contribution Decline over Time by Treatment, Linear Regression

Variables	(1) Baseline Japan	(2) R1 Japan	(3) R2 Japan	(4) Baseline Germany	(5) R1 Germany	(6) R2 Germany
Period	-0.116**	-0.0949+	-0.0712	-0.215**	-0.161**	-0.171**
	(0.0334)	(0.0544)	(0.0437)	(0.0593)	(0.0587)	(0.0649)
Constant	2.804**	2.689**	2.700**	4**	3.333**	4.456**
	(0.214)	(0.351)	(0.269)	(0.366)	(0.386)	(0.375)
Observations	330	150	240	150	120	120
R-squared	0.036	0.019	0.011	0.081	0.062	0.059

** p<0.01, * p<0.05, + p<0.1, Robust standard errors in parentheses

Note: in Japan, much less of the variation in contributions (1-4%) is explained by the Period than in Germany (6-8%)

First, we can observe that the beta coefficients of the Period variable are negative; This decline is highly significant for both control groups, as expected. For treatments R1 and R2, while the decline is significant at the p<.01 level for Germany, it is insignificant in Japan (p>.05) providing support for H2. The coefficients for Japanese R1 and R2 treatments are both below .1, while those for Germany are both above .15 lending further weight that differences here are not due to chance.

Next, we test for the end-effect itself, which we operationalize as a Mann-Whitney Test for the significant difference in mean contributions of the last two periods[65], i.e. between periods 1-8

[64] Since both the German and Japanese R2 treatments are non-normally distributed and to control for our panel data structure, we also ran random effects Tobit regression with similar results (Nelson, 1976). As contributions are doubly censored, with a lower limit of 0 and an upper limit of 5, this model reduces bias of simple linear regression. Period has a significantly negative effect on contributions at the p<.001 level. Also, previous period contributions have a significantly positive effect on contributions at the p<.001 level; the slope magnitude of the previous contributions variable shows that reciprocity is clearly taking place. As we kept in mind the contribution-to-length ratio, Tobit outputs can be made available in supplemental online material or on request.

[65] To rule out specification bias, we ran the same tests using an alternative operationalization using only the last period instead of the last two. Results are generally stronger than those reported here, implying that our chosen operationalization for the end effect in contributions is a conservative measure. However as can be seen graphically

and periods 9-10[66], respectively, for each treatment in both countries. Again, we use the robust rank-order test to confirm our results. Results are depicted below:

Table 6: Mann-Whitney Test for End-Effect of Contributions, α=.05

Mann-Whitney Test for End-Effect of Contributions, α =.05						Robust Rank Order Test	
Country	Treatment	Mean P1-8	Mean P9-10	P-Value	Z-Value	P-Value (2-tail.)	U-Value
Germany	Control	3,083	1,767	0,003**	2,938	0,012*	2,518
Germany	R1	2,740	1,292	0,000***	3,469	0,000***	3,718
Germany	R2	3,771	2,500	0,010*	2,576	0,068+	1,822
Japan	Control	2,218	1,833	0,052+	1,945	0,054+	1,927
Japan	R1	2,350	1,433	0,022*	2,287	0,024*	2,260
Japan	R2	2,333	2,208	0,640	0,467	0,668	0,429

***: p<.001; **: p<.01; *: p<.05; +: p<.1

Based on the test results, we can confirm an end-effect in Germany for all treatments, with the caveat, that using the more conservative robust rank-order test, we cannot reject the null hypothesis that the means are the same for treatment R2 (p=.068). For Japan, the end-effect is insignificant for both the control and R2 treatments at the p<.05 level and significant only in treatment R1 (p=.022). Overall, we therefore find empirical support for H2 – that there is an end-effect in Germany and less so than in Japan.

Hypotheses 3&4: Germany

Comparing the German baseline and R1 treatments over all periods, contributions over time appear fairly similar, with lower contributions in the R1 treatment particularly in the early and late phases of the game. Therefore, group representatives that cannot discuss the strategy with their constituency play more selfishly in a public good game than do individuals that are not group representatives.

from Figure 4, the end effect of the last two periods for the R1 treatment is not captured if looking only at the last period.

[66] As a robustness test, we also ran these tests with an alternate operationalization of end effect, comparing only periods 1-9 with period 10 with similar results.

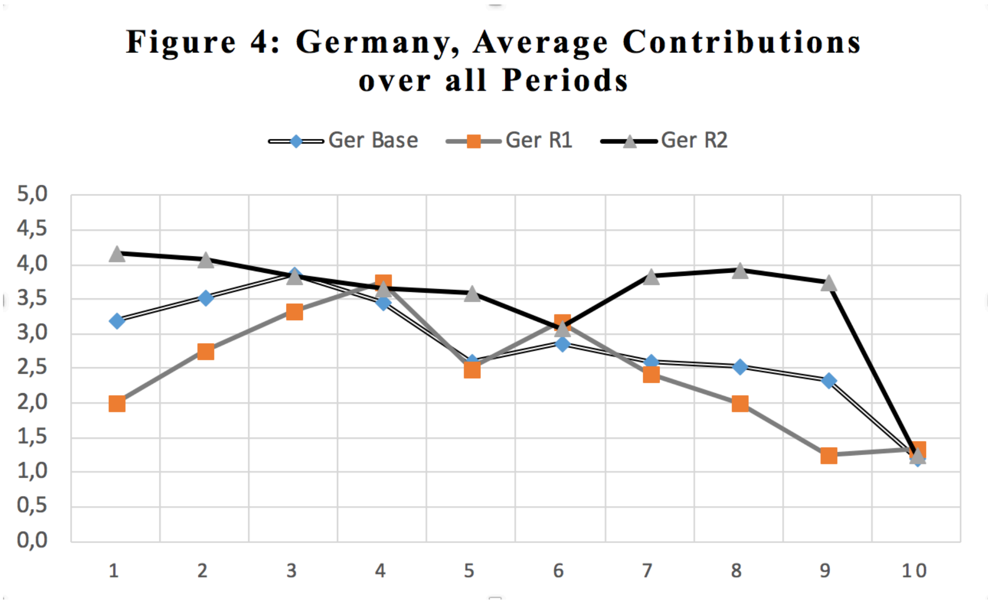


Figure 4: Germany, mean contribution over all periods

The first period of a public good game is important as it sets the stage for future interactions in terms of the degree of reciprocal behavior between the subjects. In the first period, we find that contributions in the German R2 treatment are significantly different from those in the R1 treatment (p=.019, z=2.352) but not significantly different from the baseline (p=.211, z=1.252), as can be seen in Table 5 below. First period contributions in the German R2 treatment are slightly higher than in the respective baseline and R1 treatments.

Table 5: Germany, 1st Period Contributions

		R1		R2	
	Average	P	z	p	Z
Baseline	3.200	.134	-1.495	.211	-1.251
R1	2.000	-	-	**.019***	-2.352
R2	4.167	-	-	-	-

Over all periods, we find a significant difference between contribution levels in the German baseline and R2 treatments (p=.013, z=2.483) and a highly significant difference between contribution levels in German R1 and R2 treatments (p<.001, z=4.241). While we do see a difference between the German baseline and R1 treatments in absolute terms, this difference is not significant (p=.163, z=1.394). This confirms our H3 (that R1 contributions will be lower than in the baseline) and H4 (that contributions will be higher in R2 than R1 when groups reach agreement on letting the representative pursue a cooperative strategy) for Germany.

Hypotheses 3&4: Japan

If we now look at the Japanese data, we see a different tendency. Contributions in all treatments in the first period are very similar, particularly for R1 and R2 (p=.881, z=.150).

Table 6: Japan, 1st Period Contributions

		R1		R2	
	Average	P	z	p	Z
Baseline	2.788	.583	-0.549	.660	-0.440
R1	2.333	-	-	.881	-0.150
R2	2.375	-	-	-	-

As can be seen in Figure 5 below, this result holds over all periods, where Japanese treatments do not significantly differ from each other in terms of average contributions. We confirmed these results with the rank-sum test[67].

[67] The rank-sum test shows that differences in mean contributions to the public good between the Japanese Baseline and Jap. R1 (p=.775, z=.286), between Japanese Baseline and Jap. R2 at all (p=.498, z=.678) and between Japanese R1 and Jap. R2 treatments (p=.507, z=.664) are clearly not significant. This also holds for the Robust Rank Order Test.

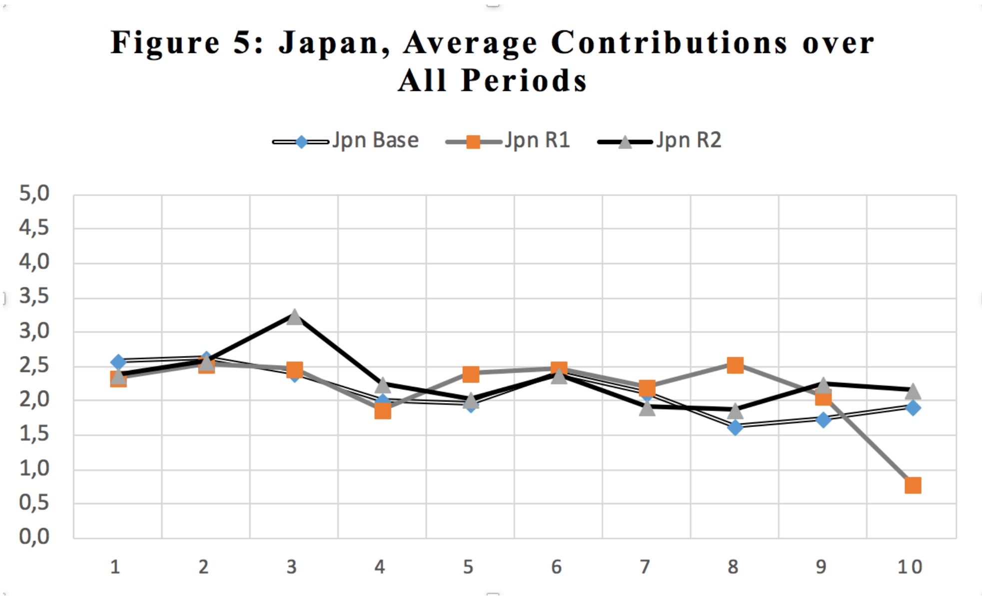


Figure 5: Japan, mean contribution over all periods

Thus, for Japan H3 and H4 are not supported.

Comparing overall contribution levels over all periods, we find that while for Germany, only the comparison between R1 and R2 is significant over all 10 periods, for Japan, the no-difference result remains the same as before. This comparison also confirms Hypothesis 4. Next, we explain the chat data analysis and report the results for Hypothesis 5 and Hypothesis 6.

4.8 Analysis of the Chat Data

After studying the chat logs for each interaction in treatments R1 and R2, we analyze the text data using a simple coding scheme. First of all, we categorize the data of each discussion in terms of whether or not subjects discussed a strategy for playing. We code everything as "strategy discussion" where some reference is made to "what to do in the game". This implies that even in the R1 treatment, where subjects did not know the exact rules of the game, they could have discussed a strategy, though only in very general terms.

Second, we observe the strategy mainly discussed or – if agreement was reached – agreed upon. Here we again apply a simple categorization scheme for coding: We distinguish between a cooperative strategy, a non-cooperative strategy and no clear strategy. Further, as this was mentioned in many groups, we count it as “cooperative” when subjects plan to start cooperatively and then react to what others do, while we count as “non-cooperative” when subjects plan to start free-riding and then react to what others do. The third category is “no clear opinion”, for groups where many different suggestions were made and no final agreement is reached.

Finally, we look at whether the group reached an agreement about a specific strategy to pursue. Again, we do this in a very simple way. If, at the end of a discussion, each of the subjects says “ok, I agree” or something to this effect, the statement is counted as having reached agreement. If the discussion continues or is stopped without such an explicit agreement, it is coded as “no agreement”.

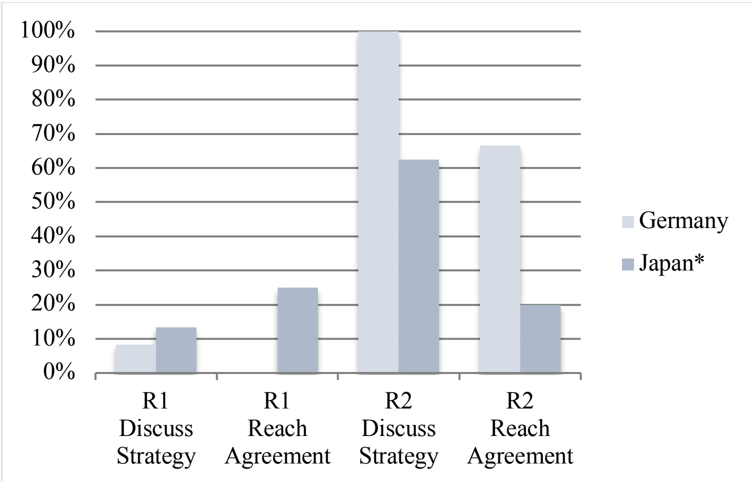
Table 7: Coding Scheme for Pre-Game Chat

#	Coded Variable	Manifested Outcomes		Chat Example
1	Was strategy discussed?	1: yes	0: no	P1: “My strategy is every-thing in B” P2: “I would say that too..”
2	Which strategy was discussed?	1: cooperative 2: no clear opinion	0: non-cooperative	P1: “So, I would suggest investing all the dollars in B and convincing the other representatives as well. What do you all think?”
3	Did the group reach agreement?	1: yes	0: no	P1: “yes, I agree” P2: “ok” P3 “OK.”

Our first category reveals no striking difference between Japanese and German subjects. In the R1 treatment, where the specific rules of the game are not yet known, only 8% of the German groups and 13% of the Japanese discuss a strategy. As subjects do not yet know the exact instructions, they cannot discuss details of a strategy. However, one group in the Japanese sample reached agreement on a general strategic orientation, referring to past experience (an experienced subject said: “being cooperative would be better for the result” and the others then replying “ok, we trust you”), but this did not occur in the German sample.

In R2, 100% of the German as opposed to 62.5% of the Japanese subjects discuss a strategy. 66% of the German groups now reach agreement on a specific strategy, but only 20% of the Japanese do.

Figure 6: Percentage of Groups that discuss strategy and reach agreement (R1 & R2)



Of those who do discuss a strategy, in Germany 75%, but in Japan only 29.03% have a tendency towards cooperation. The latter however is not because more subjects in Japan tend towards free-riding (6.45% in Japan and 8.33% in Germany), but because Japanese subjects show no clear tendency to a larger extent (64.52% in Japan and 16.67% in Germany). Of those groups who reach agreement, 75% in Japan and 87.5% in Germany vote for a cooperative strategy (25% or one group in Japan agrees on disagreement).

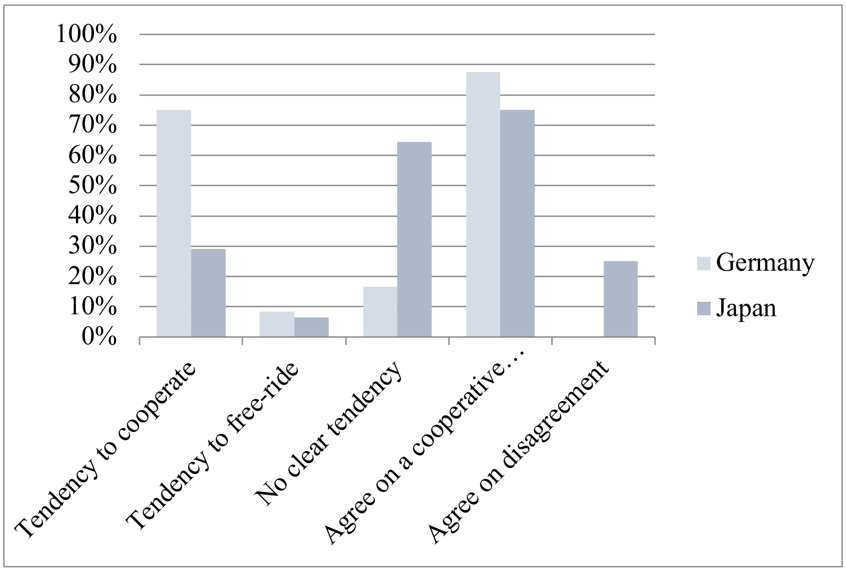


Figure 7: Strategic Tendencies of Groups in Germany and Japan (R1 & R2)

The focus on discussing and agreeing upon a strategy is much stronger in Germany than in Japan, which confirms H5. Also, German groups are indeed more frequently able to discuss a strategy (within a limited timeframe) than Japanese groups, confirming H6.

Table 8: Summary of Hypothesized and Actual Results

Hypothesis	Hypothesis based on	Germany	Japan	Finding
H1	Contributions data	✓	✓	Supported
H2	Contributions data	✓	✓	Supported
H3	Contributions data	✓	~~✓~~	Mixed
H4	Contributions & Chat data	✓	~~✓~~	Mixed
H5	Chat data	✓	✓	Supported
H6	Chat data	✓	✓	Supported

4.9 Discussion

Revisiting our research questions, we asked ourselves how contribution behavior and communication content would differ between German and Japanese subjects in our experimental setting. In summary, we find support for our basic hypotheses with respect to the differences in contribution and communication behavior between (and within) individualistic and collectivistic countries, with the caveat that two of our hypotheses, H3 and H4, are supported only in Germany.

We can show that cooperation with strangers is more easily established in the individualistic country (Germany) as compared to the collectivistic country (Japan)[68]. The flip-side of this is that individualistic subjects have no problem "betraying" trust at the end of the experiment, whereas this is different for collectivistic subjects (who presumably remain concerned with their reputation for loyalty[69]). Mainly because our Japanese subjects hardly manage to come to conclusions with respect to a strategy in the time allotted, because they need more time to build trust than our German subjects[70], chatting has less of a positive effect on contributions in Japan than in Germany. That one group in Japan agrees to disagree confirms that group solidarity can be self-defeating in public goods settings (e.g. as reported by Charness, Rigotti and Rustichini, 2007 in an experiment using the Prisoner's Dilemma). In Germany, representatives that did not talk about their strategy with their constituency assume that selfish-for-the-group behavior is what is expected from them. In contrast, we do not see this kind of behavior in Japan, which is again in line with the idea that these recently formed groups are not considered relevant in-groups for our Japanese subjects.

Our research has implications for understanding how cooperation development differs among small groups of actors embedded in different nationalities when the leap of faith involves "allowing" own group representatives to contribute to a wider public good instead of free-riding

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[68] Variance in contributions in Japan also remains fairly low over time, compared to Germany, providing further evidence that groups are more easily established in Germany, during the given timeframe.

[69] For an extreme example of loyalty in Japan, consider the *Yakuza*, who demand unconditional loyalty, with severe punishments for betrayal.

[70] One way to interpret this is that in Germany, a 5-minute chat is often enough to reduce social distance between strangers to form a minimal group in the lab, while in Japan this is more difficult due to the aforementioned cultural differences.

"for the group". Cooperation between representatives of groups and these representatives and their constituencies is critical in many business and political interactions (e.g. leadership of top management teams of multinational firms and international organizations, in cross-border mergers and acquisitions, negotiations, etc.) and is thus important to understand, also in an intercultural setting.

Yamagishi and Kiyonari (2000) argue that expectations of reciprocity from ingroup members is the source of ingroup favoritism in minimal groups. An important aspect for experimental design, but probably also for ad-hoc real-world groups is that collectivistic cultures (Japan) by far do not always act in favor of a group they are assigned to. This simple "minimal group" effect works well in individualistic cultures (Germany), but for the Japanese, these "minimal groups" in the lab have no meaning and are not seen differently from simple aggregates of strangers. Thus, group building is necessary first, whereas in the individualistic context merely belonging to an artificial group makes people act selfishly for this group. This confirms our expectations based on Yuki´s (2003) model. Further, the findings imply that team-building and negotiation between group representatives in organizations and educational settings require a longer time horizon (and thus sustained effort) in collectivistic societies.[71] Language permitting, future experiments along these lines could include treatments with mixed teams with subjects from both countries. This could allow further differentiation of cultural effects.

Future research might also explore the role of hierarchies in interacting groups negotiating for the public good, that is telling subjects in one treatment that they are on equal footing as the representative, while in another treatment, representatives are clearly framed as leaders or managers (e.g. of an imagined non-governmental organization).

[71] Thus, our groups can be regarded as proceeding through stages of the team-building process: forming, storming, norming and performing (Tuckman, 1965). While a detailed discussion of the group chats was out of scope for this paper, we did find evidence that the formation of minimal groups follows a similar pattern, especially in Germany.

The research discussed here is a first step towards meaningful intercultural comparisons in game-theoretical laboratory experiments on public goods. But, it certainly has limitations which we now discuss and provide an outlook for future research.

Limitations and Future Research

A limitation was the time-frame for communication: Even though we expected our Japanese subjects to require more time, we did not expect this effect to be so strong. Future experiments should provide longer time windows for group members to chat in order to build group cohesion and relationships and observe what happens in collectivistic cultures when groups do have "meaning" as an in-group. Also, while our samples are not perfectly balanced in size due to organizational issues, we conducted a post-hoc power analysis, which showed sufficient power to detect country-level differences.[72] Also, a limitation is that we did not measure trust on an individual level but rely on well-established external findings on studies of society-level differences in trust.

Another limitation is that some subjects seemed to have had experience participating in behavioral experiments; Thus, some subjects discussed some very general strategy in treatment R1, before reading the full instructions (for chat examples see the Appendix). Nonetheless, overall, self-selected students have been empirically demonstrated to be an appropriate subject pool for the study of social behaviour using games in the lab (e.g. Exadaktylos, Espin, & Branas-Garza, 2013). Also, the identification of specific causes of group differences in preferences via identity priming of course only works if the identity prime is actually able both to affect the salience of the specific group-level trait of theoretical interest and to affect observed behavior (van Hoorn, 2018). For this, it is (1) necessary to collect data "other than the observed behavior that testifies to the effect of the identity prime" – e.g. our detailed chat logs

[72] Since contribution means and standard deviation are known, we implemented the power analysis using Stata's *samplesi* command with the default alpha level (.05, two-sided test), which resulted in power = 1.00 (n1/n2=1.66).

which supplement our contribution data and (2) to provide evidence showing that variation in the affected group-level trait does indeed go on to affect individuals' preferences (van Hoorn, 2018). That some strategy was discussed in treatment R1 demonstrates that the chat served its purpose of increasing the salience of being a group representative and the identification with the ingroup, a goal of our experimental design. Further, this result, that pre-play communication in the absence of full instructions can have behavioural consequences is interesting for future research on public goods. That we see differences in contribution behaviour between our baseline and representative treatments testifies to the second condition (van Hoorn, 2018).

As always in laboratory research, the general question of external validity can be raised. Further research could try to establish in how far generalizations from laboratory experiments to field situations are feasible in this context – and perhaps add to the literature with field experiments. Overall, we believe that further interdisciplinary research along these lines would be fruitful both to confirm or reject our findings and to deepen our understanding of the underlying mechanisms and mediators involved in our willingness to trust group representatives. In the words of Charness, Rigotti and Rustichini (2007: 25) "group influence and social identity are important issues that can be ignored only at the peril of researchers in the social sciences".

Conclusion

For now, we can conclude that there are cultural differences in behavior of representatives of interacting groups that can be detected in the laboratory. While the robustness of individual findings will need to be confirmed by further studies, we believe that Yuki´s (2003) model can to a large part explain the behavior observed and that our results can be insightful for future studies that should improve on some of the design features of our paper and might even examine negotiations between cultures.

4.10 References (Third empirical study)

Akerlof, G.A., & Kranton, R.E., 2010. *Identity Economics*. Princeton University Press: Princeton, NJ.

Akerlof, G.A., & Kranton, R.E., 2002. “Identity and schooling: some lessons for the economics of education.” *J. Econ. Lit*. 40, 1167–1201.

Ailon, G., 2008. "Mirror, mirror on the wall: Culture's consequences in a value test of its own design." *Academy of management review, 33*(4), 885-904.

Bachmann, R., 2011. "At the crossroads: Future directions in trust research." *Journal of Trust Research, 1*(2), 203-213.

Baier, A. (1986). Trust and antitrust. *Ethics*, 231-260.

Ben-Ner, A., & Putterman, L., 2009, "Trust, communication and contracts: An experiment." *Journal of Economic Behavior & Organization, 70*(1), 106-121.

Benjamin, D.J., Choi, J.J. & Strickland A.J., 2010. "Social identity and preferences." *American Economic Review*, 100, pp. 1913-1928.

Berg, J., Dickhaut, J., & McCabe, K., 1995. "Trust, reciprocity, and social history." *Games and economic behavior, 10*(1), 122-142.

Bhattacharya, R., Devinney, T. M., & Pillutla, M. M., 1998. "A formal model of trust based on outcomes." *Academy of management review, 23*(3), 459-472.

Bigoni, M., & Dragone, D., 2012. "Effective and efficient experimental instructions." *Economics Letters*, 117(2), 460-463

Charness, G., Rigotti, L and Rustichini, A., 2007. "Individual Behavior and Group Membership." *American Economic Review*, 97(4): 1340-1352.

Chen, Y. and Xin Li, S., 2009. "Group Identity and Social Preferences." *American Economic Review,* 99(1): 431-57.

Chiao, J. Y., & Blizinsky, K. D., 2009. "Culture–gene coevolution of individualism–collectivism and the serotonin transporter gene." *Proceedings of the Royal Society B: Biological Sciences*.

Chiao, J. Y., Harada, T., Komeda, H., Li, Z., Mano, Y., Saito, D., . . . Iidaka, T., 2009. "Neural basis of individualistic and collectivistic views of self." *Human brain mapping, 30*(9), 2813-2820.

Coleman, J., 1990, Foundations of social theory. *Cambridge, Mass.: Belknap Press.*

Costa, A. C., 2003. "Work team trust and effectiveness." *Personnel Review, 32*(5), 605-622.

Croson, R., 2005. "The Method of Experimental Economics." *International Negotiation* 10: 131-148.

Das, T., & Teng, B.-S., 2004. "The risk-based view of trust: A conceptual framework." *Journal of Business and Psychology, 19*(1), 85-116.

Exadaktylos, F., Espin, A. M., & Branas-Garza, P., 2013. "Experimental subjects are not different." *Scientific Reports*, 3.

Falk, C. F., Heine, S. J., & Takemura, K. (2014). Cultural variation in the minimal group effect. *Journal of Cross-Cultural Psychology*, 45, 265-281.

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

Fiske, A. P., Kitayama, S., Markus, H. R., & Nisbett, R. E., 1998. "The cultural matrix of social psychology." In Gilbert, S.; Fiske, T., & Lindzey, G. (Eds.), The handbook of social psychology, 915-981. New York, NY: McGraw-Hill.

Frazier, M. L., Johnson, P. D., & Fainshmidt, S., 2013. "Development and validation of a propensity to trust scale." *Journal of Trust Research, 3*(2), 76-97.

Fukuyama, F., 1995. *Trust: The social virtues and the creation of prosperity*. Free Press: NY.

Furlong, D., 1996. *The conceptualization of" trust" in economic thought*: Institute of Development Studies.

Granovetter, M., 1985. "Economic action and social structure: the problem of embeddedness." *American Journal of Sociology*, 481-510.

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

Gulati, R., 1995. "Does familiarity breed trust? The implications of repeated ties for contractual choice in alliances." *Academy of Management Journal, 38*(1), 85-112.

Hall, E. T., & Hall, M. R., 1990. *Understanding cultural differences: Germans, French and Americans* (Vol. 9): Yarmouth, ME: Intercultural Press.

Han, Shihui, 2016. *Culture, self, and brain: Handbook of advances in culture and psychology*, *6*, 77-112.

Harada, T., Li, Z., & Chiao, J. Y., 2010. "Differential dorsal and ventral medial prefrontal representations of the implicit self modulated by individualism and collectivism: An fMRI study." *Social Neuroscience, 5*(3), 257-271.

Hauge, K. E., & Rogeberg, O., 2015. "Representing Others in a Public Good Game." *Games, 6*(3), 381-393.

Hofstede, G., Hofstede, G. J., & Minkov, M., 2010. *Cultures and Organizations: Software of the Mind* (3rd ed.). New York, NY: McGraw-Hill.

van Hoorn, A., 2014. "Individualism and the cultural roots of management practices." *Journal of Economic Behavior & Organization*, 99, pp. 53-68.

House, R. J., Hanges, P. J., Javidan, M., Dorfman, P. W., & Gupta, V., 2004. *Culture, leadership, and organizations: The GLOBE study of 62 societies*: Sage publications.

Iida, Y., & Schwieren, C., 2015. "Contributing for Myself, but Free riding for My Group?" *German Economic Review, 17*(1), 36-47. doi:10.1111/geer.12069

Isaac, R. M., Walker, J.M. and Williams, A., 1994. "Group size and the voluntary provision of public goods: Experimental evidence utilizing large groups", *Journal of Public Economics*, 54, 1-36.

Knack, S., & Keefer, P., 1997. "Does social capital have an economic payoff? A cross-country investigation." *The Quarterly journal of economics*, 1251-1288.

Kong, D. T., 2013. "Intercultural experience as an impediment of trust: Examining the impact of intercultural experience and social trust culture on institutional trust in government." *Social indicators research, 113*(3), 847-858.

Kosfeld, M., Heinrichs, M., Zak, P. J., Fischbacher, U., & Fehr, E., 2005. "Oxytocin increases trust in humans." *Nature, 435*(7042), 673-676.

Kuwabara, K., Willer, R., Macy, M. W., Mashima, R., Terai, S., & Yamagishi, T., 2007. "Culture, identity, and structure in social exchange: A web-based trust experiment in the United States and Japan." *Social Psychology Quarterly, 70*(4), 461-479.

Ledeneva, A., 2008. "Blat and guanxi: Informal practices in Russia and China." *Comparative studies in society and history*, *50*(1), 118-144.

Li, P. P., 2013. "Entrepreneurship as a new context for trust research." *Journal of Trust Research, 3*(1), 1-10.

Minkov, M., 2017. "A revision of Hofstede's model of national culture: old evidence and new data from 56 countries. *Cross Cultural & Strategic Management*, Vol. 25 Issue: 2, 231-256.

Merritt, A., 2000. "Culture in the Cockpit Do Hofstede's Dimensions Replicate?" *Journal of cross-cultural psychology, 31*(3), 283-301.

Mitchell, L. E., 2001. "Importance of Being Trusted." *The BUL Rev., 81*, 591.

Nelson, F.D., 1976. "On a General Computer Algorithm for the Analysis of Models with Limited Dependent Variables." *Annals of Economic and Social Measurement*, 5, pp. 493-509.

Oyserman, D. & Lee, S.W., 2008. "Does culture influence what and how we think? Effects of priming individualism and collectivism." *Psychological Bulletin*, 134, pp. 311-342.

Pan XS, Houser D. 2013. "Cooperation during cultural group formation promotes trust towards members of out-groups." *Proceedings of the Royal Society B* 280: 20130606.

Porta, R. L., Lopez-De-Silane, F., Shleifer, A., & Vishny, R. W., 1996. *"Trust in large organizations* (w5864)." Retrieved from: http://scholar.harvard.edu/files/shleifer/files/trust.pdf

Pinter, B., Insko, C. A., Wildschut, T., Kirchner, J. L., Montoya, R. M., & Wolf, S. T. (2007). Reduction of interindividual–intergroup discontinuity: The role of leader accountability and proneness to guilt. *Journal of Personality and Social Psychology*, 93, 250-265.

Rode, J., 2010. "Truth and trust in communication: Experiments on the effect of a competitive context." *Games and economic behavior, 68*(1), 325-338.

Rotter, J. B., 1980. "Interpersonal trust, trustworthiness, and gullibility." *American psychologist, 35*(1), 1.

Saparito, P. A., Chen, C. C., & Sapienza, H. J., 2004. "The role of relational trust in bank–small firm relationships." *Academy of Management Journal, 47*(3), 400-410.

Skorbiansky, S.R. 2018. "Investing in communication: An experimental study of communication in a relational contract setting". *Journal of Behavioral and Experimental Economics*. Vol. 74, June, 85-96.

Smith, P.B. and Bond, M.H., 1999. *Social Psychology Across Cultures* (2nd Ed). Boston, MA: Allyn and Bacon.

Sztompka, P., 1999. *Trust: A sociological theory*: Cambridge University Press.

Tajfel, H., Billig, M., Bundy, R. P. and Flament, C., 1971. "Social categorization and intergroup behavior,'' *European Journal of Social Psychology*, **1**, 149-178.

Triandis, H.C., 1995. *Individualism and Collectivism*. Boulder, CO: Westview.

Trompenaars, F., & Hampden-Turner, C., 1998. *Riding the waves of culture*: McGraw-Hill New York.

Tuckman, B. W., 1965. "Developmental sequence in small groups." *Psychological Bulletin, 63*(6), 384-399.

Welzel, C., 2014. *Freedom Rising; Human Empowerment and the Quest for Emancipation*, Cambridge University Press.

Wildschut, T. & Insko, C. A. (2007). Explanations of interindividual-intergroup discontinuity: A review of the evidence. *European Review of Social Psychology*, 18, 175-211.

Williamson, O. E., 1993. "Calculativeness, trust, and economic organization." *Journal of law and economics*, 453-486.

Yamagishi, T., Cook, K. S., & Watabe, M., 1998. "Uncertainty, Trust, and Commitment Formation in the United States and Japan." *American Journal of Sociology, 104*(1), AJSv104, 165-194.

Yamagishi, T., and Kiyonari, T., 2000. "The Group as the Container of Generalized Reciprocity." *Social Psychology Quarterly*, 63(2): 116–32.

Yamagishi, T., 2011. *Trust: The Evolutionary Game of Mind and Society*. New York: Springer.

Yuki, M., 2003. "Intergroup comparison versus intragroup relationships: A cross-cultural examination of social identity theory in North American and East Asian cultural contexts." *Social Psychology Quarterly*, 166-183.

Yuki, M., Maddux, W. W., Brewer, M. B., & Takemura, K., 2005. "Cross-cultural differences in relationship-and group-based trust." *Personality and Social Psychology Bulletin, 31*(1), 48-62.

Yuki, M. & Takemura, K., 2014. "Intergroup Comparison and Intragroup Relationships: Group Processes in the Cultures of Individualism and Collectivism." In Yuki, M. & Brewer, M. (eds.) *Culture and Group Processes*. New York: Oxford University.

Zucker, L. G., 1986. "Production of trust: Institutional sources of economic structure, 1840–1920." *Research in organizational behavior*.

4.11 Appendix A: Chat Examples

Time left	**R1 Chat** (Translated)**, Unit 1 - Group #3** (before game)
294	hi
289	hi
280	short introduction round
270	who is the third person in the group?
267	very funny..to discuss/coordinate on something, if one does not know what one is supposed to do…
266	hi
256	precisely…
250	**therefore one cant really coordinate**
241	I'm excited too
210	me, I dont like risk
204	probably we should act more loyal to our groups if we get to know each other beforehand
197	:-)
188	could of course be the case
176	**risk..well..it depends on the trade-offs**
174	**I try to decide very rationally, using expected utility**
173	certainly evesdropping
168	:-)
151	**expected utility is always good**
149	that they are recording and evaluating this chat is clear
141	**sounds good to me**
139	**agreed**
115	**well in the Prisoner's Dilemma I usually give people a trust advance and try to cooperate**
96	in the worst case the others each more money ;-)
90	hehe
79	**I think, everyone should decide on their own**
75	I dont think it makes sense to think about it yet now
72	participating helps the students in general because it increases our (university) research funding
51	ok..but it is totally unclear (what we're supposed to discuss)
20	we'll see what happened
4	have fun
1	**so far my head was in the game in every experiment, wait and see**

Time left	**R2 Chat1** (Translated)**, Unit 1 - Group #1** (before)
297	Hello
279	also Hello
266	**So I would say, it is best to invest everything in b**
250	**So, I would suggest investing all the dollars in B and convincing the other representatives as well. What do you all think?**
241	**I would say the same - no matter what, everything in B, should give the biggest profit**
235	the loss one has/would have when the others do not invest in b is worth the risk
227	**definitely**
226	what you said [player #] s3
223	I think so too
203	Then we seem to agree, right?
196	Of course it would be bitter if they all invest in a, but that is worth the risk
161	**Good, then the representative has to convince the others only to invest everything in B. Best profit for all: 6.75 Talers versus 3 Talers total profit**
147	**One would just have to give it a try, but the profit that everyone has when you invest in B is bigger at the end - and all people start with the same preconditions**
116	Most people here in the experiment are reasonable, that is what I learned from my experiences here so far
97	**I do not believe it [player] s1: if someone is the only to invest in a, he collects the most compared to others**
60	**So, no matter who we represent. The task will be to convince the others of "Everything in B". if it does not work, bad luck.**
60	The risk would be worth it and then to reevaluate the strategy after the first round.
30	So, rather, take a small residual risk and be able to look one's self in the mirror
26	but then we can not communicate anymore [after round 1]
19	**ok, so everything in b**
14	**I agree**
9	**everything in B**
3	**Let's try it.**
1	ciao

Table 9: Pre-Game Chat, Detailed Examples (German Representative Treatments)

Period	Mean	Std. Dev.	Min	Max
T=1	2,556	1,942	0	5
T=2	2,694	1,836	0	5
T=3	2,681	1,912	0	5
T=4	2,097	1,863	0	5
T=5	2,000	1,906	0	5
T=6	2,417	1,774	0	5
T=7	2,056	1,883	0	5
T=8	1,931	1,771	0	5
T=9	1,958	1,674	0	5
T=10	1,736	1,884	0	5

Table 10: Contributions: Basic Statistics (over all Treatments: Japan)

Period	Mean	Std. Dev.	Min	Max
T=1	3,128	2,154	0	5
T=2	3,462	1,998	0	5
T=3	3,692	1,852	0	5
T=4	3,615	1,756	0	5
T=5	2,872	2,067	0	5
T=6	3,026	1,871	0	5
T=7	2,923	2,018	0	5
T=8	2,795	2,123	0	5
T=9	2,435	2,186	0	5
T=10	1,256	1,743	0	5

Table 11: Contributions: Basic Statistics (over all Treatments: Germany)

Major (Q9)	Freq.	Percent	Cum.
1: Economics or Business	96	40,51	40,51
2: Humanities	38	16,03	56,54
3: Other Social Sciences	46	19,41	75,95
4: Engineering or IT	20	8,44	84,39
5: Unspecified	20	8,44	92,83
6: Natural Sciences	13	5,49	98,31
7: Psychology	4	1,69	100,00
Total	237	100,00	100,00

Table 12: Distribution of Majors

4.12 Appendix B – Instructions

Dear Participant,

Thank you for participating in this experiment in decision making.

INSTRUCTIONS

This is an experiment in decision making. You will be paid for your participation.

The amount of money you earn will depend on the decisions made by you and the other decision-makers.

At no point in the experiment will you be asked to reveal your identity to anyone. Your name will never be associated with your decisions. To keep your decisions confidential, please do not reveal them to any of the other participants.

At this moment, we will give you 3 euros for arriving on time. All money that you earn from now on will be yours, and your earnings will be paid to you in cash at the end of today's experiment.

THIS EXPERIMENT

In this experiment, you will be in a group of three people. In the first stage of the experiment, you will have time to meet the members of your group and talk to them via a messenger program for five minutes. In the computer screen you will see soon, you can type any question or comment that you would like to make to the other members of your group.

In the second stage of the experiment, a representative from your group will play an interactive game with representatives from the other groups in the experiment. You may or may not be chosen to represent your group. If you have been chosen to represent your group will be shown to you on the screen. Before the first stage starts, you will be given the instructions for the game in the second stage.

(In the last stage of the experiment, you will again meet the members via Messenger for five minutes.)

*This is used only in the R3 treatment

Some general advice before the experiment begins:

If you have any questions during the experiment, please raise your hand and wait until the experimenter comes to your table.

Do not communicate with any of the other participants except when the experimenter asks you to do so.

Payment will be based on your performance during the experiment. It will be paid to you privately and in cash after the experiment has concluded.

Do you have any questions?

(Move to the instructions for the second part)

INSTRUCTIONS FOR THE SECOND PART

During the second part, a representative from your group interacts with representatives from the other groups in the room. The screen will indicate whether or not you have been randomly selected to represent your group.

If you have been selected to represent your group, you will interact later with representatives from the other groups.

If you have not been selected to represent your group, you will be asked to complete a short questionnaire.

The representatives will play 10 rounds. Only after these 10 rounds have been completed will you be told the outcome of their play.

New representatives will then be selected to play another 10 rounds following the same rules. You and your group members will receive payments based on the decisions taken by the representatives of the groups during the experiment.

INSTRUCTIONS FOR REPRESENTATIVES

You have been selected to represent your group. You will now interact with representatives from the other two groups in the laboratory.

You and your group members will receive payments based on the decisions you make in your interaction with the other representatives. You will interact for 10 rounds and make 10 decisions. The structure of the interaction is as follows:

You will be asked to make a series of decisions about how to allocate a set of tokens. You interact with the representatives of the other two groups in this laboratory.

You will not be told the identities of the others with whom you will interact. For each decision, you will have five tokens to allocate. You must decide how many of these tokens you wish to invest in project A and how many you wish to invest in project B. The amount of money you earn depends on how many tokens you invest in project A, how many you invest in project B, and on how many the other representatives invest in project B.

EXAMPLE OF DECISIONS THAT YOU WILL MAKE IN THIS EXPERIMENT

Each decision that you make will be similar to the following:

Example: Each of the three representatives has five tokens to allocate. You (and your group) will earn 1 cent for each token that you invest in project A. For each token that you invest in project B, you (and your group) will earn 0.75 cents and the other representatives (and their groups) will earn 0.75 cents (a total of 2.25 cents for all of you together). For each token that the other representatives invest in project A, their respective group will earn 1 cent. For each token that the other representatives invest in project B, this representative and associated group will earn 0.75 cents and you and your group will earn 0.75 cents (a total of 2.25 cents for all of you together). In summary, you (and your group) will earn:

1 cent multiplied by the number of tokens you invest in project A

+0.75 cents multiplied by the number of tokens that you invest in project B

+0.75 cents multiplied by the number of tokens that the other representatives invest in project B

Any amount you earn now, as a group representative, will be divided equally among you and the other members of your group. The cents in this experiment are converted into € in the following manner: 1 cent = 0.02€ .

If you have any questions now, please ask the experimenter. If you have no questions and we can start, please press ‘ok.’

*Test starts.

*Chat starts.

*PG game starts.

4.13 Appendix C – Questionnaires

Identification

(1) I have positive feelings towards my team members

(2) I have confidence in my team members

(3) I feel comfortable depending on my team members

(4) I think the other team members performed well

(5) I think that, generally speaking, I have more in common with the members of this team than with the members of the other teams

(6) I trust all of the members of my team equally well

Answers to the identification questions were based on a 6-point Likert scale.

Accountability

(7) I feel accountable for my actions in this experiment.

(8) I feel that my group members hold me accountable for my decisions.

(9) If things don't go the way they should, my group members will be angry with me.

(10) If things go well, my group members will be happy with me.

(11) The success of my group members depends on me.

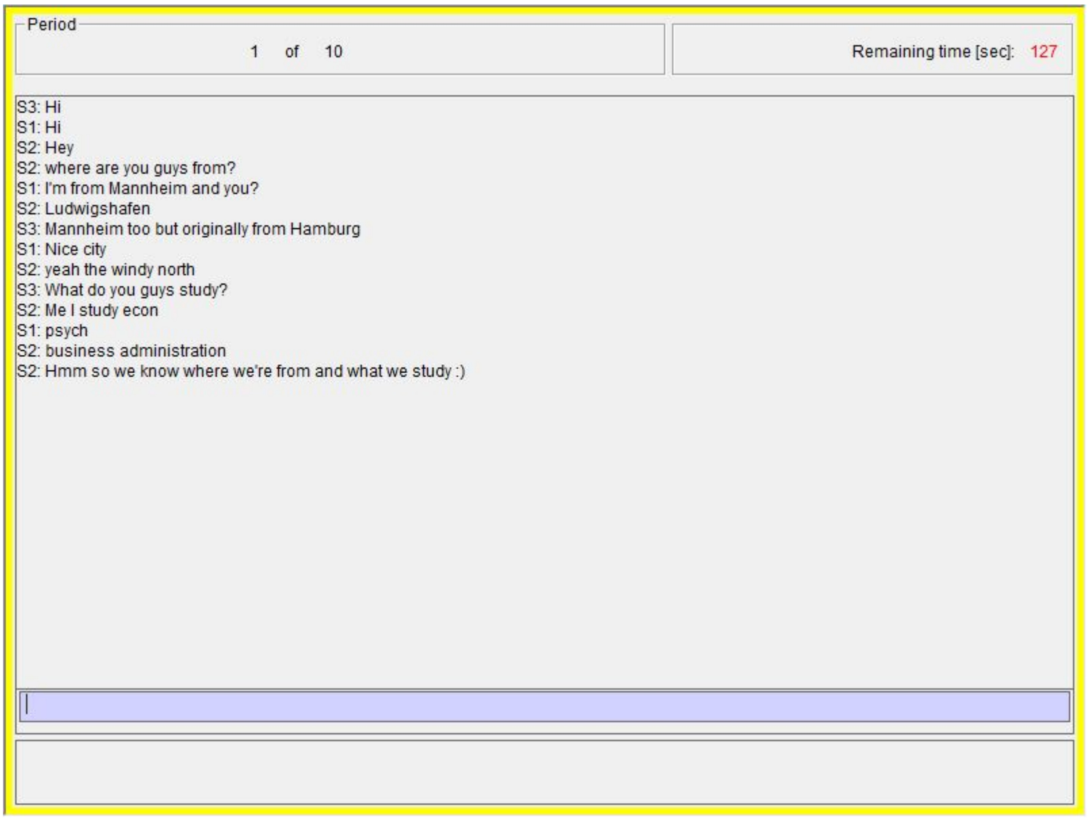
(12) I feel that I would like to be able to explain why I did certain things in this experiment.

(13) Overall, my efforts in this experiment were very important.

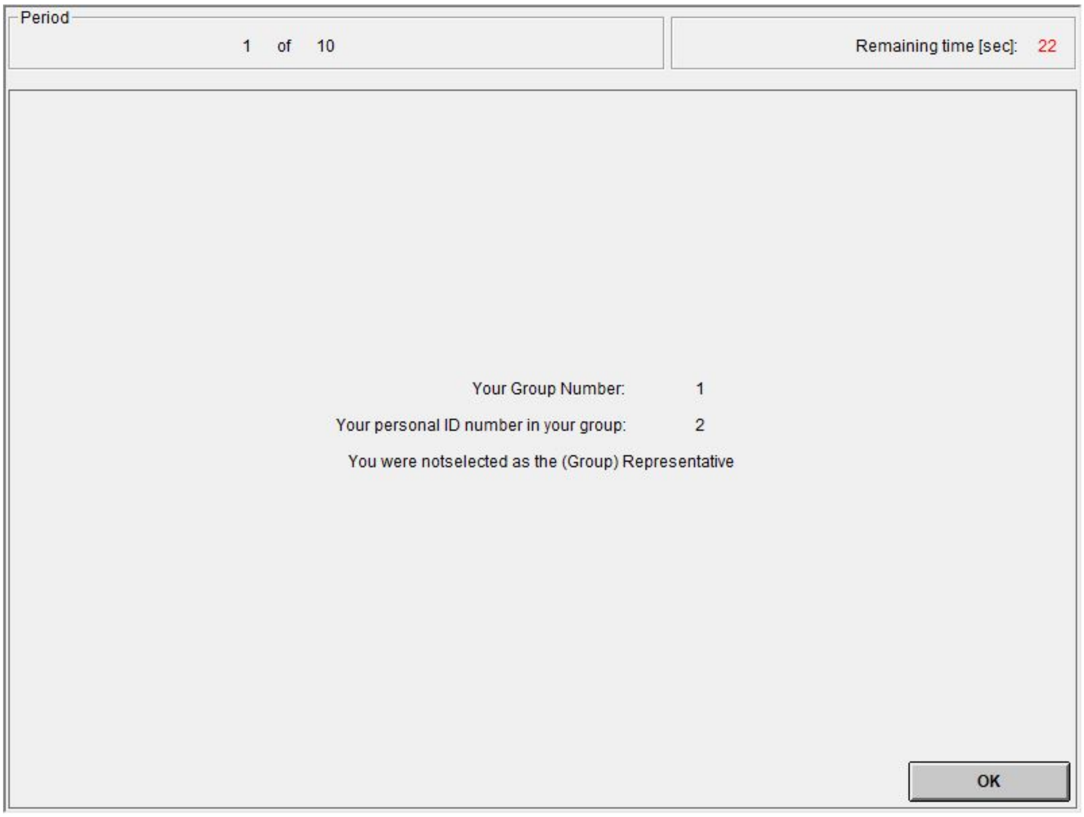
Answers to the accountability questions were based on an 8-point Likert scale.

4.14 Appendix D – Screenshots from the Game

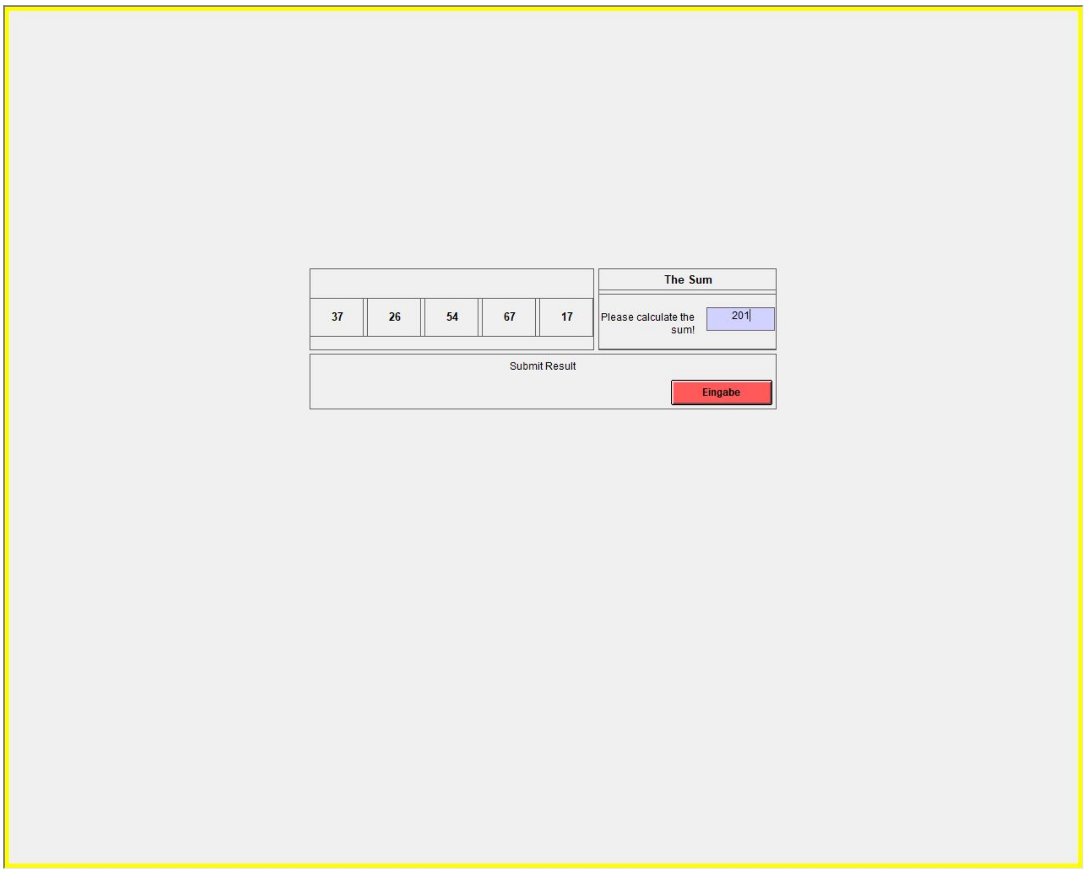
C.1 Group Chat Window (Example from Treatment R1)



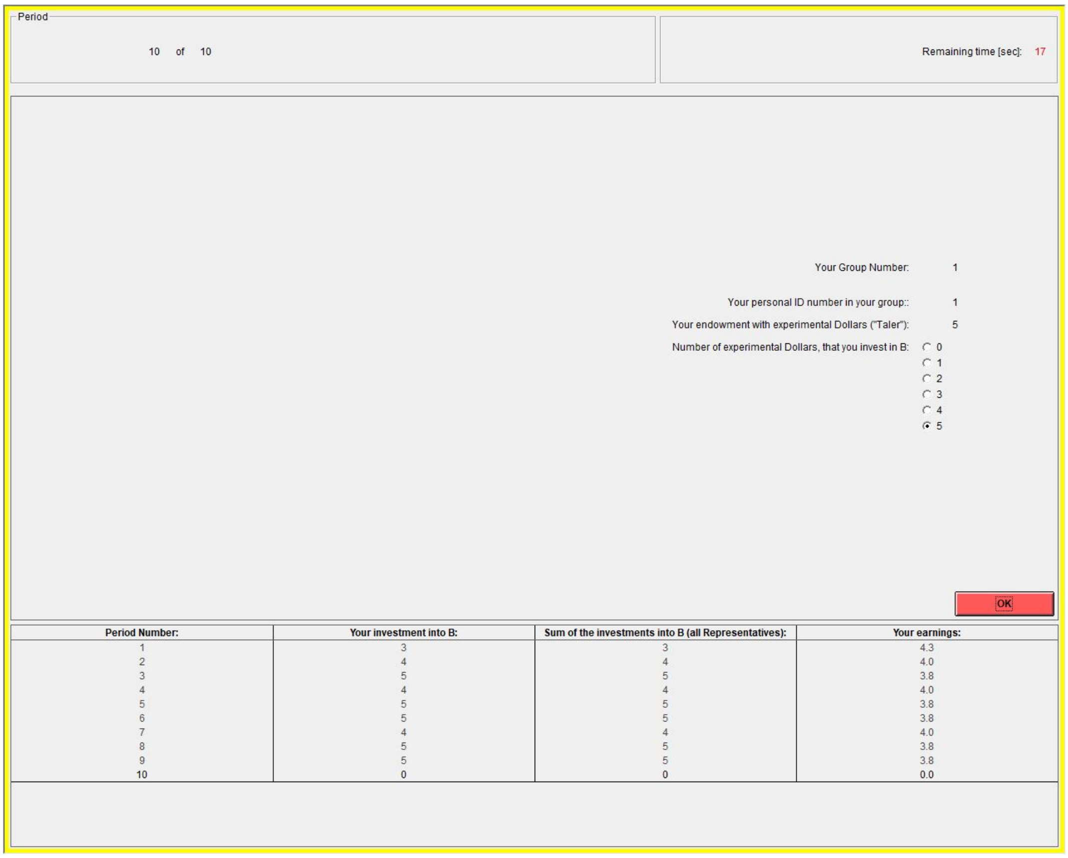
C.2 Information Screen for those not selected (R1 and R2)



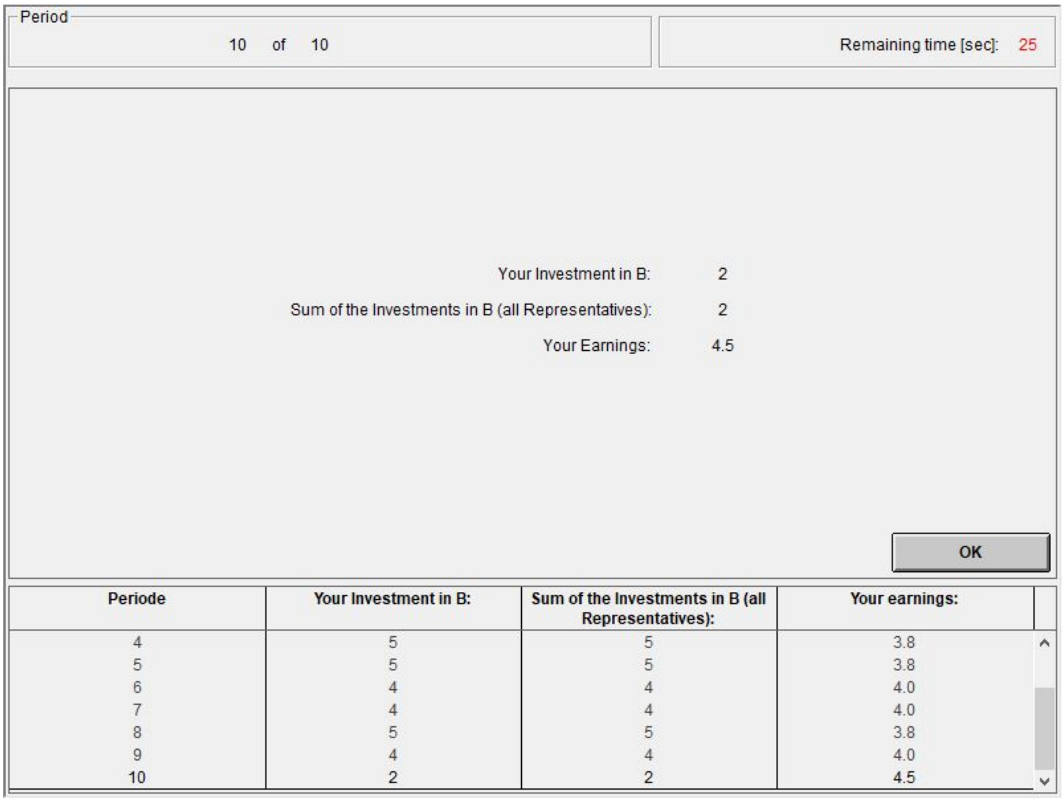
C.3 Simple Calculation Task (for non-representative group members in Treatments R1 and R2)



C.4 Allocation Decision Screen for Group Representatives (R1 and R2)

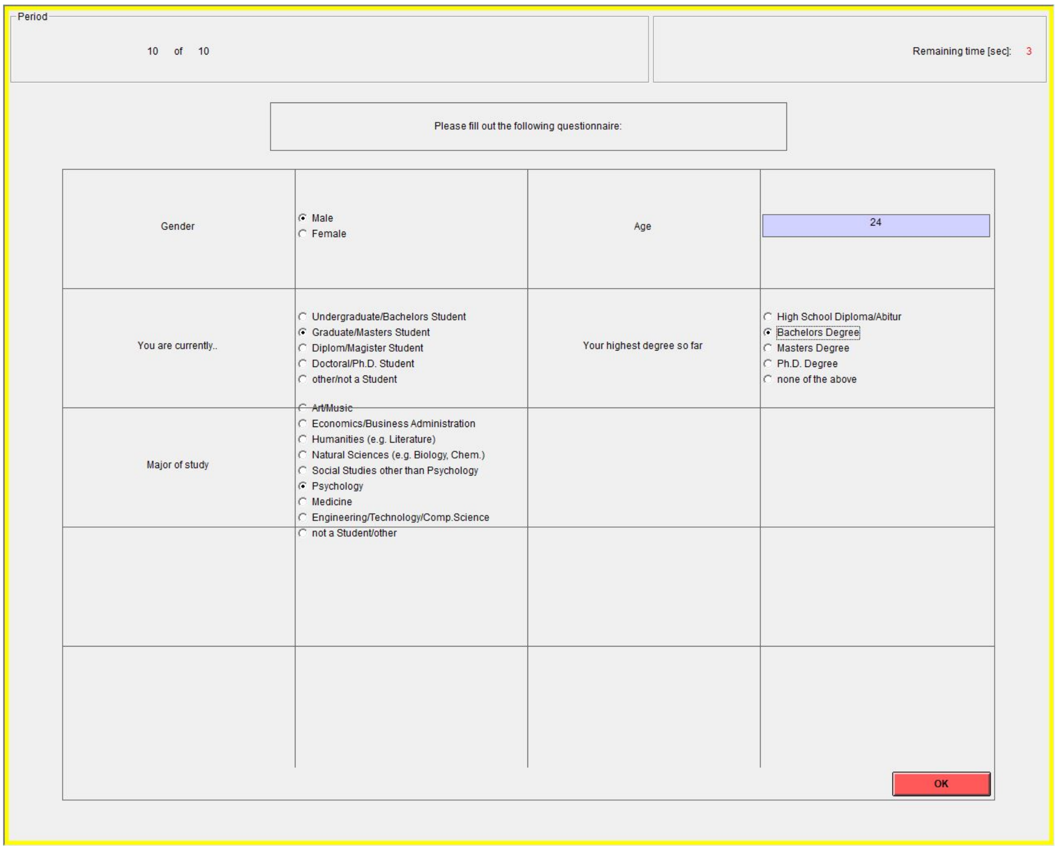


C.5 Feedback Screen for Group Representatives (R1 and R2, example from Period 10)[73]



[73] The screenshots provided were taken for illustrative purposes with three test players-- the “Sum of the Investments in B column” here would normally take on values from 0-15, not just 0-5.

C.6 Collection of Demographic Information (after Period 10)



4.15 Appendix E – Additional Tables and Figures

Table 7: Correlation Matrix

	Contribution	Session	Period	End Effect	Gender	Age	Major
Contribution	1						
Session	-.14841168	1					
Period	-.18646811	9,71E-15	1				
End Effect	-.15623251	-1,99E-15	.69631062	1			
Gender	-.02788849	-.17040416	0	3,89E-14	1		
Age	.09244858	-.49540854	-6,28E-16	2,82E-15	.1336589	1	
Major	.00578531	-.00894251	2,30E-15	-1,27E-15	-.05076093	.11503041	1

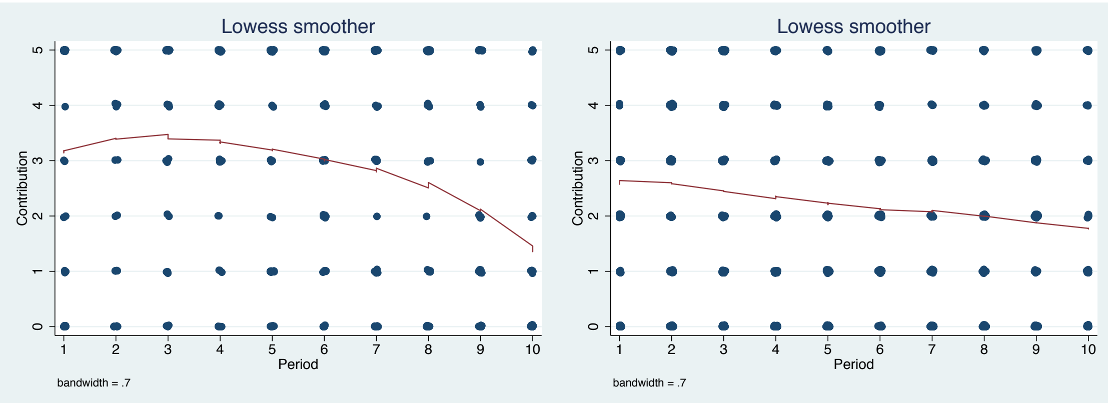


Figure 6: Contributions Over Time in Germany and Japan (Lowess Smoothing with Jitter)

The Random-Effects Tobit Model

To appropriately account for the doubly censored nature of the dependent variable of our model (contributions to the public good are both left and right censored, i.e. contributions have a lower limit of zero and an upper limit of 5) and to thus obtain unbiased, consistent and efficient estimates of the parameters, we use the censored Tobit estimation procedure (Amemiya, 1973[74]; Nelson, 1976). Since some subjects typically free ride, but others contribute to the public good, our dependent variable Y will contain a significant number of zero observations as well as many positive observations between 1 and 5. A panel data model offers two distinct advantages over the traditional linear regression model. First, a panel model can capture both cross-sectional

[74]Amemiya, Takeshi, 1973. "Regression Analysis when the Dependent Variable is Truncated Normal," *Econometrica*, Econometric Society, vol. 41(6), pages 997-1016, November.

and time-series variation in the dependent variable under investigation. Secondly, this type of model is able to measure not only the effects of observable variables on the dependent variable, but also the effects of relevant unobservable or non-measurable influences. Observable variables are incorporated into the model in the usual manner. The means by which the unobservable variables are incorporated depends upon whether a fixed-effect (FE) or random-effects (RE) model is used in estimation. The RE model assumes that the unobservable (i.e. non-measurable) factors that differentiate cross-section units are best characterized as randomly distributed. As subjects vary by their gender, age, major of study and many other factors, it seems quite reasonable to assume that the differences between them are randomly distributed. As such, we feel that the use of the RE model is well suited for analyzing contribution behaviour. The resulting RE model is presented below:

$$\mathbf{Y_{ij} = \alpha + \beta_1\ PreviousContribution + \beta_2\ Period + \beta_3\ Session \ldots + \sigma(v)_i + \sigma(u)_I},$$

where i indexes the subjects in our analysis and t the time series units, e.g. the *period* of the game, such that t={1,2…10}. *PreviousContribution* captures the effect of the contribution from the last respective period on the current period. *Session* controls for multiple sessions of a given treatment. *EndEffect* is described in the main body of the paper. *Gender, Age* and *Major* of study are self-explanatory. For readability, σ(v) and σ(u) are omitted from the tables.

Table E.8:End Effect in Japan vs Germany, Random Effects (Censored) Tobit Regression

	Japan			Germany		
Model	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Baseline	R1	R2	Baseline	R1	R2
Previous Contribution	0.197+	0.402+	0.0270	0.561*	0.378*	0.624+
	(0.104)	(0.210)	(0.124)	(0.264)	(0.165)	(0.377)
End Effect	-0.642*	-2.070**	-0.280	-3.881**	-1.974**	-4.832**
	(0.322)	(0.694)	(0.370)	(1.075)	(0.634)	(1.545)
Session	0.0268	-0.532	-0.0298	-30.65	-0.110	-2.262
	(0.711)	(1.314)	(0.571)	(876.9)	(0.640)	(1.853)
Constant	1.460	8.434	2.521	33.85	2.465	17.27
	(8.217)	(17.69)	(4.904)	(876.9)	(2.325)	(10.53)
Observations	330	150	240	150	120	120
Individuals	33	15	24	16	12	12

Dependent Variable: P.G. Contributions
Standard errors in parentheses
** p<0.01, * p<0.05, + p<0.1

Table E.9: (bivariate) Country-Level Treatment Effects, R.E. (Censored) Tobit Regression

	Pooled		
	(1)	(2)	(3)
VARIABLES	Baseline	R1	R2
Country	-1.192	-0.833	-2.614*
	(0.893)	(0.923)	(1.184)
Constant	3.225**	2.644**	4.827**
	(0.739)	(0.683)	(0.969)
Observations	480	270	360
Individuals	49	27	36

Standard errors in parentheses; Country: 0=Germany, 1=Japan
** p<0.01, * p<0.05, + p<0.1

Table E.10: Japan, Results using R.E. Tobit Panel Regression

	Japan				
	(1)	(2)	(3)	(4)	(5)
VARIABLES	Baseline	R1	R1 w. Demogr.	R2	R2 w. Demogr.
Previous Contr.	0.164	0.415+	0.443*	0.00322	0.00429
	(0.101)	(0.215)	(0.221)	(0.122)	(0.122)
Period	-0.177**	-0.206*	-0.209*	-0.137**	-0.138**
	(0.0439)	(0.0962)	(0.0973)	(0.0507)	(0.0507)
Gender			-2.773+		-1.184
			(1.683)		(1.386)
Age			1.072**		0.572
			(0.366)		(0.408)
Major			0.129		0.714*
			(0.220)		(0.343)
Session	0.0206	-0.518	-2.100+	-0.0309	0.0129
	(0.722)	(1.300)	(1.108)	(0.577)	(0.564)
Constant	2.573	5.832	-4.394	3.100+	-10.47
	(4.032)	(9.721)	(7.605)	(1.635)	(8.510)
Observations	330	150	150	240	240
Individuals	33	15	15	24	24

DV = Contributions to the Public Good; Standard errors in parentheses
** p<0.01, * p<0.05, + p<0.1
Note: for the representative treatments, three times as many participated (e.g. 45 and 72, respectively), but only the representatives contributed for their respective group and are thus relevant for Stata

Table E.11: Germany, Results using R.E. Tobit Panel Regression

	Germany				
	(1)	(2)	(3)	(4)	(5)
VARIABLES	Baseline	R1	R1 w. Demogr.	R2	R2 w. Demogr.
Previous Contr.	0.669*	0.550**	0.462**	0.883*	0.999**
	(0.276)	(0.175)	(0.136)	(0.430)	(0.323)
Period	-0.659**	-0.283**	-0.277**	-0.818**	-0.869**
	(0.155)	(0.0880)	(0.0855)	(0.242)	(0.244)
Gender			-0.151		4.555**
			(0.666)		(1.699)
Age			-0.136+		-0.0755
			(0.0746)		(0.185)
Major			0.437*		-0.526+
			(0.171)		(0.311)
Session		-0.0570	0.449	-1.996	-4.189*
		(0.547)	(0.554)	(1.665)	(1.774)
Constant	5.698**	2.980+	3.850	16.52*	27.71**
	(1.468)	(1.531)	(2.361)	(8.012)	(10.37)
Observations	150	120	120	120	120
Individuals	15	12	12	12	12

Standard errors in parentheses
** p<0.01, * p<0.05, + p<0.1

5. The contested Market for Bitcoin trading: A cross-national comparison of the Role of Institutional Voids and Corruption

Abstract

We study the interplay between institutions, institutional voids and corruption on the development of the emerging but highly contested market for digital currencies. Digital currencies are rapidly expanding in scope and popularity with the potential for fundamental yet controversy-provoking changes to the financial industry and beyond. Building on institutional theory, we theorize how institutional voids in conjunction with corruption determined the attractiveness of the market for digital currencies by analyzing the market for Bitcoin trading from 2013 to 2017 in 46 countries. Contrary to our expectations we find that corruption is negatively related to bitcoin trading and that institutional voids facilitate rather than hamper the amount of bitcoin trading. Our study contributes to a better understanding of the role of institutional voids for the development of a new contested market. Our findings may empower corporate and institutional entrepreneurs as well as policy makers to better serve this market (e.g. by filling identified gaps and combating possible negative externalities) and thus master the digital transformation.

Keywords: Institutions, Institutional Voids, Corruption, Corruption perception index (CPI), Bitcoin trading, Cryptocurrencies, National culture

JEL Classification: E42; E58; L51; O11; O17; O1

Authors: This paper was written in collaboration with Prof. Dr. Suleika Bort. With respect to the distribution of work, the following declaration can be made: The basic research idea as well as the theoretical model has been developed by both authors but with the lead of Andrew Isaak. The dataset has been conceived of, developed and managed by Andrew Isaak and Prof. Dr. Suleika Bort. Overall, Andrew Isaak is the main corresponding author of this work.

Project History (extract): A prior version of this article was accepted for presentation at the 2018 G-Forum (Entrepreneurship) Conference in Stuttgart, Germany and has been submitted to the AOM 2018 Specialized Conference on Startups in Tel-Aviv, Israel. The article will ultimately be submitted for consideration to Administrative Science Quarterly (VHB: A).

The contested Market for Bitcoin trading: A cross-national comparison of the Role of Institutional Voids and Corruption.

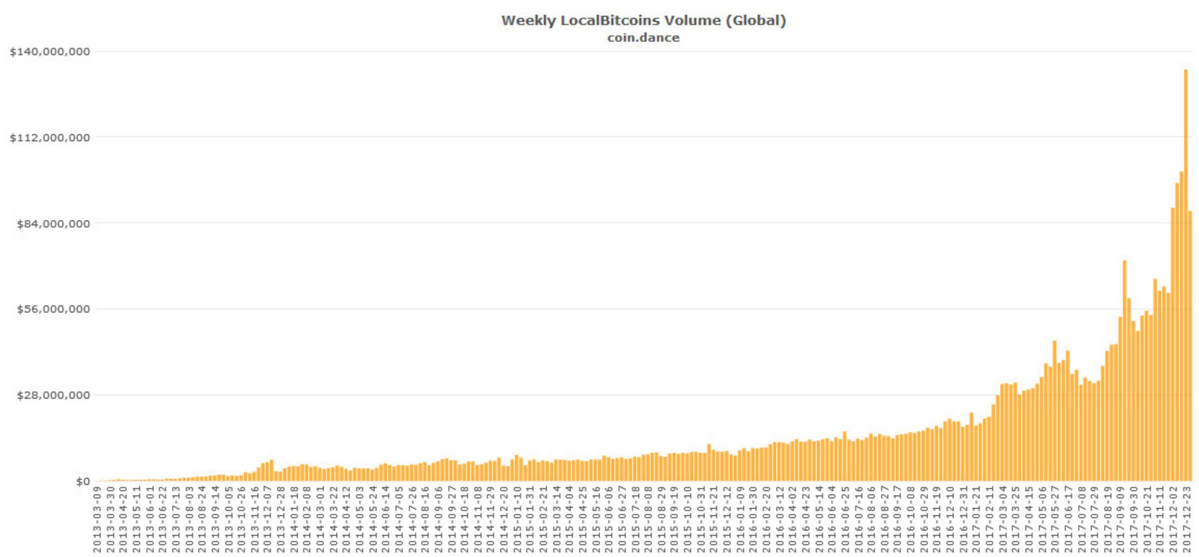
5.1 Introduction

Organization theorists have recently paid considerable attention to the emergence and development of new industries (Padgett & Powell 2012; Navis and Glynn, 2010; Georgallis et al., 2018). For example, prior research has investigated how policy shifts and the state impact the emergence of the solar photovoltaics (PV) industry in Europe (Georgallis et al., 2018) or the biotechnology industry in the US (Powell et al., 2012). A common issue of emerging industries is that their legitimacy is often highly contested (e.g., Rao 1998), which makes it difficult to judge the attractiveness of the new industry. The discussion of digital currencies is highly contested since on the one hand their trading has been commonly stigmatized as a criminal artefact, while on the other hand they are viewed as the future of banking (Bariviera 2017). Digital currencies, such as Bitcoin, have the potential to disrupt not only existing payment systems but also to change entire monetary systems (Böhme et al. 2015).

In the situation where regulations and standards are highly unevenly distributed or even absent, - i.e., the presence of institutional voids which are characterized by the absence of institutions that shape market transactions, that is the relative lack of intermediary firms, regulatory systems and contract-enforcing mechanisms (Khanna and Palepu 2000; Khanna and Rivkin 2001), what enables such a contested emerging industry to develop? On the one hand, recent institutional theory research suggests that the lack of institutions results in high uncertainty. For example, Khanna and Palepu (1997) argue that institutional voids are likely to hamper economic exchange in the capital, labor and product markets of emerging economies. An environment that lacks effective political governance and regulatory institutions may facilitate corruption or theft to conduct business. On the other hand, institutional voids present opportunities for entrepreneurs – a space to engage in (often innovative) profit maximization without the shackles of regulatory authorities (Mair & Marti 2009).

In this paper, we bring together these two perspectives and examine the conditions under which institutional voids offer opportunities or constrain behavior. In particular, in this explorative study, we examine the emergence and development of a new contested market: the market for digital currencies (i.e., Bitcoins). Digital currencies, are rapidly expanding in scope and popularity, bringing with them the potential for fundamental changes to the financial industry and beyond. For several years, Bitcoins were only something for technical nerds or gamers. However, recently a rapid growth process emerged, and in early 2018 cryptocurrency market capitalization surpassed the $700 billion mark[75], with an estimated $2 billion transactions per day with Bitcoins alone[76]. Below, the development of Bitcoin trading from 2013 through 2017 is depicted for a frequently used global platform (localbitcoins.com).

Figure 1: Bitcoin Trading Volume from 2013-2017



[75] http://www.businessinsider.de/bitcoin-price-global-cryptocurrency-market-capitalisation-january-3-2018-1?r=US&IR=T

[76] https://www.forbes.com/sites/ktorpey/2017/11/20/bitcoin-now-processes-2-billion-worth-of-transactions-per-day-a-10x-increase-in-2017/#6c4274212fba

Note: BTC transaction volume has since declined from this peek value to the level of mid-year 2016 where it has remained for the last 6 months:
https://blockchain.info/charts/n-transactions

While the period between FY2013 and FY2016 is marked by steady growth, this is better described as exponential in FY2017, which was confirmed to us in an interview with the platform's founder, a recognized expert of the field: "Currently we are processing about 30000 trades each day and it has been going up. I think last year because of the huge growth in volume, there was growth from 10000 trades early 2017 to 20 or 30 thousand trades on normal days, on weekends it is less" (F1: 3).

Organizations have also responded to this trend. For example, Ebay is seriously considering accepting Bitcoins (BTC) as a payment method (Dec. 2017). Efforts involving established banking industry players are taking place globally to make Bitcoins a feature of mainstream financial services (*Financial Times*, 2014). Governments and citizens of developing countries are placing large hopes on digital currencies as a means not only to mitigate poor financial infrastructure and to reduce transaction costs but also as a potential remedy for corruption via disintermediation. At the same time, such innovations are placed within institutional voids which opens the possibility of fraud and abuse. Specifically, the largely anonymous mechanisms are attractive to illicit sectors of the economy as a way to launder money earned through the drug trade and other means. Thus, Bitcoin trading is still a highly contested setting characterized by the lack of an institutional framework that regulates the market, further fueling the tensions about the legitimacy of Bitcoin trading.

In research, the topic has also gained some importance. For example, in the *Academy of Management Journal*, Dodgson et al (2015) single out bitcoins and digital money as a fresh new research area in management. The authors explain that digital money *dematerializes* by moving (even more) cash transactions to the digital world and at the same time *disintermediates*, bringing money and people closer together (Dodgson et al, 2015). At the same time, we know little about the role of institutions in this context, for which cross-national comparison should be particularly helpful. For example, Mair, Marty and Ventresca (2012) call for papers exploring impact in settings with particularly complex and/or underexplored institutional contexts. Similarly, Stephan, Uhlaner and Stride (2015) based on a study in 26 nations, advocate greater consideration of institutional configurations in institutional theory and comparative entrepreneurship research. Yet, to our knowledge, little or no work has been done on this topic in top journals in organization studies, management or even entrepreneurship to date. We aim to bridge this gap by exploring the interlinkages between the growth in bitcoin trading, the level of institutional development and corruption. While several theoretical lenses come to mind in order to examine the topic under study, institutional theory and imperfect markets can be particularly insightful when examining corruption cross-nationally (e.g. Anokhin and Schulze, 2009; Mair, Marty and Ventresca, 2012; Puffer, McCarthy and Boisot, 2010).

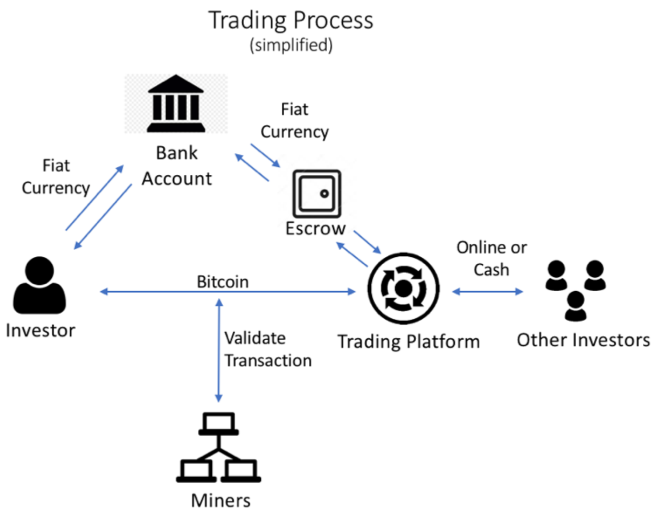
The rest of the paper is structured as follows: we first explain our empirical setting, after which we define institutional voids and corruption, followed by our methodology, analysis and results which are then discussed in the light of extant literature. Finally, we conclude with limitations of our approach and suggestions for future research.

5.2 The Empirical Setting for Bitcoin trading

Localbitcoins is a platform launched in early 2013 with the mission of covering cities worldwide with Bitcoin trading, with a particular focus on developing countries: "The mission of localbitcoins was always bringing bitcoin everywhere (…) We wanted to enable access to bitcoin in each city, everywhere in the world." (F1:2) "The main idea of the service was to enable access to bitcoin everywhere." (F1: 2). For countries such as Venezuela and Ghana, until late 2017, the platform was often the only option available:

"Localbitcoins is kind of a place which works when the other exchanges don't work, so in countries where there is limited access to centralized exchanges and so on" (F1: 2). Asked to elaborate, the founder interviewed went on to say that "most of the time it's just that the country doesn't have really good financial infrastructure and there aren't any centralized exchanges in such country. For example, in an African country it might be really difficult or pretty much impossible to send or even to have an account in Coinbase [a key website for transmitting digital coins]" (F1: 2).

Figure 2: The Trading Process



To trade on Localbitcoins, users are given a free and secure online wallet (e.g. two factor authentification, encrypted database) when signing up, after which they have two options to conduct trades (1) trade locally in cash in the local currency and (2) trade online in the local currency. If the users trade in cash, they typically indicate a preferred meeting location in their local city and provide their phone number along with the minimum and maximum amount of Bitcoins available for the transaction and their requirements of the buyer (e.g. identification). If the user elects to trade online, both parties commit to the use of the escrow service. Once the buyer clicks on 'buy' and selects his or her payment method, the buyer is given 90 minutes to make the payment to the third-party Escrow account. If the payment is not made, the transaction is cancelled and the buyer receives negative feedback unless he convinces the seller otherwise. In the usual case, that the payment is made within the time window, the funds are released to the seller as soon as the Bitcoin transfer is verified (the average Bitcoin transaction time is approximately one hour, but can last anywhere from 10 minutes to 24 hours[77]). Localbitcoins charges 1% of the transaction volume in fees for the escrow service, the platform's primary business model: "the escrow service (…) that's where we make the money" (F1: 2). The founder went on to specify that "the escrow service has always been like 99% of the revenues" (F1: 2). For the online trade, the buyer must also follow the seller's terms of trade, which typically include email and SMS verification (i.e. linking a buyer to a unique phone number and Sim Card), providing photo identification, having a bank account in the seller's country and having conducted a set number of previous transactions (e.g. 25 previous trades) on the platform with positive feedback over a certain period of time (to prevent fraud, typically, accounts should be in existence for at least 30

[77] https://coincentral.com/how-long-do-bitcoin-transfers-take/
The transaction time also depends on the fee the selling is willing to pay, as higher fees allow for faster transactions as miners typically select the most profitable transactions first.

days). Sellers are also initially limited to five ads until they reach certain transaction thresholds. Trading restrictions for both parties are successively lifted as these gather a number of trades under their belt and reputation-score milestones.
The platform uses a so-called open limit order book model, where sellers decide on a price and amount range (minimum and maximum they are offering at the given price) and the offer is typically valid until fulfilled unless the seller removes the ad. When setting the price of an ad, sellers typically look at the current average Bitcoin price (e.g. as determined by Bitstamp) and incorporate their experience with local buyer's willingness to pay (e.g. local demand). Buyers typically sort trades by price and select the best price among sellers with their preferred payment option and a good reputation.

Localbitcoin targets first-time customers in particular: "Our target market is the first-time buyer" (F1:2). When asked to elaborate, the interviewee stated "the majority of them [platform users] might be bitcoin investors that might be doing a little bit of bitcoin trading on the side. This situation is kind of common" (F1: 2). Professional Bitcoin traders especially in the first three years of the platform's existence were typically experts in their mid 30s, often with an international background who would trade or promote Bitcoins on the side of their regular employment. When asked about Bitcoin meetups and hackathons in different parts of the world, the founder replied: "The people you would meet all over the world [from 2013 to about 2015] were quite similar. Expats, male, white like in their 30s no matter where you go. There were some locals but mostly experts, the international focus people" (F1:2).

5.3 Theoretical Background and Hypotheses

5.3.1 The emergence of the contested market for bitcoin trading

New industries, are defined by those "business environments in an early stage of formation" (Santos and Eisenhardt 2009: 644). Contested industries have been defined as industries that face widespread disapproval because some sectors of society find them "offensive, inappropriate, or harmful" (Davidson 2003: 2). Previous research has identified contested industries such as arms (Durand & Vergne, 2015) or the tobacco industry (Simons et al., 2016). New and contested markets are often ill-structured and their development is uncertain (Navis and Glynn, 2010) and there is evidence that cryptocurrencies such as bitcoin have the features to be viewed as a new contested industry.

In 2008, in the middle of the world's latest financial crisis, one or several anonymous creative minds, under the pseudonym "Satoshi Nakamoto", devised the idea of creating a new currency: one that is independent of institutions such as banks, central banks and investment companies and is more direct, faster and more transparent than traditional currency systems. In this sense, Bitcoins are currently "sustained by sociological features that are directly at odds with the political ideology of the theory of money that underpins it (Dodd 2017). The Bitcoin system relies upon a decentralized network in order to verify all the transactions via a public ledger (i.e., the block chain). Currently, Bitcoins are not directly backed by a government or a central bank and are therefore truly decentralized (Weber 2014). The number of bitcoins is limited to 21 million, which are successively mined by performing complex calculations.[78] The underlying price of a bitcoin is therefore based on both the cost involved in mining the coins as well as on this artificial supply shortage. While a growing number of cryptocurrencies exist, the Bitcoin algorithm remains a dominant design in this new market (Geroski, 2003).

This increasing virtuality of transactions is akin to a further disassociation of money from physical reality, posing both risks and benefits. On the one hand, the increasing anonymity made possible by blockchain transactions makes this innovation interesting for money launderers, criminal organizations and for tax evasion. For example, Bouri et al. (2017a) scrutinize safe haven and hedging properties of Bitcoin; in a related paper, the authors hypothesize that the digital currency is used to hedge global uncertainty (Bouri et al, 2017b). In fact, the value of bitcoin gained ground (or spiked) during the Cyprus financial crisis of 2013[79], lending further credence to this hypothesis. On the other hand, this technology holds

[78] Note, these calculations need a lot of energy. According to a study from ING Bank, one Bitcoin-transaction equals the monthly energy demand for a one-person household.

[79] https://www.forbes.com/sites/petercohan/2013/04/02/are-bitcoins-safer-than-cyprus/#13cacb9152f2

the promise of reducing transaction costs and of spurring additional novelties and recombinations of products and services to create customer value. Thus, consider how coin mining leads to markets for specialized mining rigs and hardware wallets for (encrypted) safekeeping of digital assets.

A recent literature review of entrepreneurial finance points to bitcoins and crowdfunding as signs of changing institutional conditions (Cumming & Vismara, 2017). While some countries, such as Japan, have legalized bitcoin as a currency and where it is already possible to pay energy bills and food such as Sushi with Bitcoins, other markets such as China have taken drastic measures to forbid trading entirely, while much of the world has yet to regulate this novel market. This was confirmed by the (now infamous) bitcoin entrepreneur we spoke to: "Yeah, well…we have some discussions ongoing all the time with different regulators and offices around the world. Mostly (at least) for us [our platform], there haven't been that many restrictions" (F1: 4). These contrasting institutional (and cultural) environments are likely to have different effects on the growth and development paths of bitcoin and on cryptocurrencies in general. One key difference in these environments is corruption, the economic cost of which has been estimated at $2.9 trillion.[80]

5.3.2 Regulative Institutions and Entrepreneurial Activities

In analyzing the emergence of new industries, Aldrich and Fiol (1994) distinguish between cognitive legitimacy, or the degree to which the knowledge about a new industry is diffused in a society, and sociopolitical legitimacy, which refers to the extent to which a new industry is seen as appropriate and right by the general public, key stakeholders, government people and opinion leaders (see also Scott 2001 and Suchman 1995). One type of sociopolitical legitimacy that directly affects the emergence of new industries is the regulative dimension which entails

[80] https://globalanticorruptionblog.com/2015/12/22/where-does-the-2-6-trillion-corruption-cost-estimate-come-from/

“rule setting, monitoring, and sanctioning activities” (Scott, 2001: 52). These rules are set by powerful actors, such as the state or other regulative organizations. These rules have the ability to define what is acceptable and what not in a given society. They regularize and constrain behavior (Scott, 2001: 51) and they have a strong impact on the emergence of a new industry. For example, Aldrich and Fiol (1994: 655) refer to the example of the emergent pay-per-call information-services industry (using 900-prefix phone numbers) which was growing rapidly in the early 1990s in the US. However, the development of this industry slowed down because it lacked consistent government regulations and uniform standards. In addition, prior institutional research has, for example, studied the role of regulative institutions for the genesis of the solar photovoltaics (PV) industry in Europe (Georgallis et al., 2018) or the biotechnology industry (Powell et al., 2012). Also, the emergence of the Biotechnology industry was slowed down by strong regulations that were perceived as hindering the growth of the biotech industry in the US (Aldrich and Fiol 1994: 662). The German biotechnology industry was also hampered by a hostile regulatory environment for genetic research throughout the 1980s and early 1990s. Only strong regulative changes for example the liberalization of genetic testing regulations in 1993 and beginning in 1995 the introduction of substantial technology promotion programs, led to the growth of the German biotechnology industry.

There is also strong empirical evidence that both formal institutions play a role in enabling entrepreneurship (e.g. Sephan, Uhlaner and Stride, 2015). Entrepreneurs are often conceptualized as exploring and exploiting the nexus of opportunity (Shane, 2003) in their respective environments (March, 1991). Eventually, institutional entrepreneurs enter the fray in new markets and “leverage resources to create new institutions or transform existing ones” (Maguire, Hardy and Lawrence, 2004: 657). Institutions can constrain as well as foster entrepreneurial opportunities. Eckhardt and Shane (2003: 336) define entrepreneurial opportunities “as situations in which new goods, services, raw materials, markets and organizing methods can be introduced through the formation of new means, ends, or means-ends relationships. These situations do not need to change the terms of economic exchange to be entrepreneurial opportunities, but only need to have the potential to alter the terms of economic exchange."

For example, Sine and David (2003) explain how changes in the environment impact entrepreneurial opportunities in the US electric power industry. The authors argue that environmental jolts enable search processes and led key actors to reformulate existing regulatory institutions, thereby developing entrepreneurial opportunities.

Institutional Regulations and Bitcoin Trading

Scholars have begun to study the emergence of new markets. One theme centers on the emergence of new market categories (Navis and Glynn, 2010) and the role of state-based regulation (Georgallis et al., 2018). Although this work explores how regulation impacts the emergence of a new industry in a cross-national setting, a few studies address how strong regulative institutions versus their absence impacts the emergence of new markets.

Changes in government regulations can raise or lower the attractiveness of a new industry as it alters the incentives for all players in the affected sector. However, on the one hand, if regulations provided a supportive legal environment and financial support and thus lower entry barriers for a new sector, prior research shows that new firm foundings in the new sector increase (Sine et al. 2005). Yet, if government regulations are missspecified, they may lower the entrepreneurial opportunities.

5.3.3 The regulation of Bitcoins

Bitcoins were developed to ensure a high level of transparency and with no apparent influence from lawyers or regulators. Their trading includes tools to facilitate honest participation (Böhme, et al 2015). Thus, besides the common underlying software (the Blockchain), Bitcoin trading does not build on a common governance structure which distinguishes Bitcoin trading from conventional payment systems. This has several implications for the functioning of the system (see Böhme et al., 2015: 219): First, with Bitcoin trading there is no need for a financial institution, payment processor, or other intermediary to verify a user's identity. Second, in contrast to credit card networks which normally do not permit unlawful transactions in the place of sale, Bitcoin imposes no such prohibition on the sale of particular items. Finally, Bitcoin payments are not reversable because the protocol has no possibility to change an unwanted or an accidental purchase.

During our extensive interview on the topic, the founder explained: "Of course it [the legal status] is quite unclear but that is the situation for the regulators most of the time. Regulation right now [2018] looks a little better since there is a new European Union directive coming this year and it will be much more clear in the European Union compared to previously" (F1: 1). We therefore assume that perceived uncertainty is a crucial factor mitigated by legal regulation. While we expect that partial legalization or light regulation would reduce such uncertainty, without negatively effecting trading volume, when governments take a strong stand and decisively restrict or outright ban the use of Bitcoins, we would expect to see a reduction in trading. In the words of the founder of the trading platform under study "In this kind of businesses or industry like finance, this way to do business or move money or wealth it is always about the regulation" (F1: 1).

We therefore posit that:

H1: Strong legal regulation will be negatively related with Bitcoin trading volume over time.

5.3.4 Emerging Market Status and Bitcoin Trading

> *"Of course localbitcoins is kind of a place which works when the other exchanges don't work, so in countries where there is limited access to centralized exchanges and so on" (Interview with Jeremias Kangas, Founder of Localbitcoins.com on July 4th, 2018)*

While a comparatively large share of innovations originate from developed countries, developing countries stand to benefit disproportionately from them, particularly when these are not yet regulated and their control is decentralized (as in the case of cryptocurrencies). Developing countries are faced with often systemic challenges, such as inequality, climate change, limited resources, corruption and in many cases phases of social unrest. The diffusion and application of innovative digital and financial technologies can contribute to promoting greater access to resources and technologies to people who currently have no such access. At the same time, due to globalization, developing countries can face strong competitive pressures. New markets can provide a potential pathway for such countries to more quickly catch up with developed countries in individual sectors of the economy by leapfrogging over outdated technologies (e.g. Brezis & Krugman, 1997; Fudenberg, Stiglitz & Tirole, 1983 and Goldemberg, 1998). Therefore, some African countries have skipped the development of landline phone infrastructure in favor of the direct move to the use of newer technology - mobile phones. Similarly, Kenya has used M-Pesa (a type of mobile phone bank account) to compensate for a comparatively poorly developed financial infrastructure and banking system. In China, entire cities have been constructed as test-markets for solar photovoltaic at scale, considered a future (renewable) energy technology with the potential to replace fossil fuels and nuclear energy (e.g. the city of Rizhao). According to the industrial organization literature, lower wages in emerging countries may lower the cost of entry for emerging countries to take advantage of new industries which can lead upstart metropolitan areas to rapidly overtake major cities (Brezis & Krugman, 1997). At the same time, developed countries can be comparatively slow to adopt new market developments, since they are typically market leaders in extant markets (with the corresponding economies of scale in production) and at the same time typically have much higher wages, making rapid entry into new markets somewhat cost prohibitive.

Finally, a related motive for some developing markets to enter new and contested markets is that of survival (e.g. the economic crisis in Venezuela which has led to a liquidity problem).

Meanwhile, in developed countries, cryptocurrency trading is clearly not motivated by either leapfrogging or survival. US and UK citizens typically have higher incomes and are therefore likely to engage in cryptocurrency trading on the side, with mainstream investments going into classical stock and bond markets. Inhabitants of developed countries are much less likely to depend on such new markets for survival – this type of activity (e.g. speculative risks using disposable income) can therefore for all intents and purposes be considered a luxury in such settings. We therefore posit that:

H2: The country's emerging market status will be positively related with Bitcoin trading volume over time.

5.3.5 Corruption and Bitcoin Trading

Transparency International defines corruption as "the misuse of public power for private benefit" (Transparency International, 2010a). Consider a startling statistic: 96% of bitcoins are owned by only 4% of investors (formally: addresses)[81] – a large portion of the wealth is concentrated in few hands. Power concentrates more easily if there is little or no controlling/regulatory entity (e.g. Lukes, 2004), as is currently the case with bitcoins.

According Kaufmann et al. (2009: 4) corruption can be defined as "the extent to which public power is exercised for private gain" and includes such activities as bribery, cronyism, nepotism, patronage, graft and embezzlement. The theoretical foundation for the relationship between corruption and conducting business in a country focuses on the increase in costs associated with corrupt practices—that is, whether or not an entrepreneur gets involved in corrupt activities (e.g., Becker 1968). In this context, conducting a criminal act depends on the expected value of

[81] https://news.bitcoin.com/bitcoin-numbers-21-statistics-reveal-growing-demand-cryptocurrency/

negative outcomes (costs) as well as on the probability of getting caught and prosecuted. Thus, if entrepreneurs assume that the legal framework is strong and the restrictions are high, they will be less likely to be involved in corrupt activities. Since Bitcoins developed anonymously and are often classified as non-legal currency they have been accused of supporting illegal transactions[82].

Prior research has reported several areas for illicit activities in the context of Bitcoin trading (see for example, Böhme et al. 2015). For example, the early adopters of Bitcoin were marketplaces in the internet that valued greater anonymity and the absence of rules concerning what could be bought or sold (for example the online sale of drugs). Prior research found that the transaction volume grew sharply when these marketplaces introduced Bitcoin. Christin (2013) reports that the turnover on the Silk Road anonymous online marketplace, the first to support Bitcoin transactions exclusively, reached $15 million per year just one year after it began operations. In addition, gambling sites also find Bitcoin attractive, in order to protect customer privacy and to receive money from customers unable to use other payment methods. Finally, Bitcoin has been used to evade international capital controls such as in China or Argentina.

In addition, in April 2018 Interpol opened a first Working Group on the Cryptocurrencies and the Darknet[83]. Of course, we expect cultural norms to play a large role here; if corruption in a country is perceived as commonplace and lighter types of corruption such as tax evasion or small bribes to facilitate business transactions are perceived as typical or as only a minor transgression with few or no social sanctions, we would expect this to impact the respective level of bitcoin trading. Thus, we assume:

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[82] This could indeed be the case if the parties remain anonymous throughout the transaction process or if there is a mafia-like structure underlying an account where it is hard to trace back ownership or control to an individual; since many bitcoin trading platforms require the use of real names, anonymity is partial at best. Certainly, the speed of both legal and illegal transactions can be greatly accelerated with blockchain technology. Speed is often a factor in success of a crime; burglars do not want to stick around for the authorities. Criminals may also use cryptocurrencies for money laundering of proceeds from drug trade or illegal gambling.

[83] https://www.interpol.int/News-and-media/News/2018/N2018-022

H3: The level of perceived corruption in a country is positively related to the country's Bitcoin trading volume over time.

5.3.6 Corruption and strong regulative institutions

Work in institutional theory mainly investigates the impact of institutions on organizational behaviour. Recent research recognizes not only the central role that institutions play in shaping economic actions but also their absence. In particular, research in institutional theory has increasingly focused on institutional voids and how firms in emerging markets handle and overcome a lack of institutions (Gao et al. 2017) or respond to different levels of institutional voids (Narooz & Child, 2017). Institutional voids are often manifested as "gaps between formal rules and norms, and their enforcement in daily practice" (Rodrigues 2013: 14). Khanna and Palepu (1997: 42) explain that there are three main sources that describe institutional voids

(1) information problems (2) missing or misguided regulations and (3) inefficient judicial systems. The lack of institutions results in high uncertainty: It is easier to engage in corruption or theft to conduct business in such an environment that lacks effective political governance, and regulatory institutions (e.g. enforcement).

We assume that the level of institutional voids moderates the link between corruption and bitcoin trading. In countries with a high level of perceived corruption, institutional voids create opportunities for entrepreneurship (e.g. Puffer, McCarthy and Boisot, 2010). As previously mentioned, we expect two mechanisms to play a central role in bitcoin adoption – (1) social norms and the legal framework and (2) enforcement.

Thus, we assume:

H4: Strong legal regulation of bitcoin trading will positively moderate the relationship between corruption and the level of Bitcoin trading over time.

5.3.7 Corruption and emerging markets

Since we expect the direct effects of both corruption and emerging market status on trading volume to be significantly positive, for mathematical reasons, we would expect the interaction of these independent variables with our dependent variable (Bitcoin trading volume) to be positive as well, i.e. that corruption will positively moderate the relationship between emerging market status and trading volume.

If we are in a developing country and –on top of this– one with a high (perceived) level of corruption, we would be intuitively more likely to trade even more with Bitcoins to circumvent the respective corrupt government. In some developing countries it is relatively normal to pay bribes to government officials for simple bureaucratic tasks (e.g. in certain parts of India, see Bertrand et al, 2007[84]).

At the same time, many emerging countries have a large income gap between the rich and the poor (and corresponding effects on access to health and education, e.g. Mohanty and Pathak, 2009, Seven and Coskun, 2016). Cryptocurrency trading can give people in such countries hope of escaping the low income trap.

If, on the other hand, we are located in an 'advanced' country (with comparatively high education levels and average income and a reasonable inflation level allowing significant accumulation of disposable income), we would expect another regime to take precedence underlying the motivation to engage in Bitcoin trading, e.g. that investors seek to earn income beyond their normal salary by engaging in high-risk speculative bets, a luxury permitted by their stable economic situation.

In advanced countries, citizens can more easily invest parts of their disposable incomes (e.g. into the stock market) without risking not being able to pay their monthly rents. At the same time, corruption is likely to be significantly lower overall and is therefore less likely to have an

[84] For more recent studies in other regions see Blundo et al (2013), Kwong (2015) and Obydenkova & Libman (2015).

effect on a given individual. Further, in advanced countries, institutions are often further developed (see for example, Wright et al, 2005) which we would expect to dampen the effect of corruption on individual traders. We therefore posit:

H5: The country's emerging market status will positively moderate the relationships between corruption and the level of Bitcoin trading over time.

5.4 Sample Description

We utilize a full sample of data on Bitcoin trading volume spanning 46 countries with individual currencies, covering the years 2013-2017 from the bitcoin trading platform www.localbitcoin.com. This platform, founded in 2012 by two brothers – both technology entrepreneurs - is based in Helsinki, Finland.

We selected Localbitcoins for as our primary data source for several reasons: first, it is the platform which is most well-known to be used to trade digital currencies (particularly Bitcoin) in developing countries and not just developed countries, allowing us to observe regions and countries that would otherwise not be observable. Second, the data was publicly available at the time of writing, allowing the replication of results. In addition, we were able to interview the founder to clarify the intricacies of the dataset and the history of and users of the platform. Further, Localbitcoins' decentralized model, particularly the reliance on cash transactions in local cities, gives us confidence that the majority of trades were conducted in a particular country.

5.5 Description of Dependent, Independent and Control Variables

5.5.1 Dependent Variable

Our dependent variable is the natural log of the weekly trading volume in US-Dollars per country per week. Since our dependent variable is highly skewed (the skewness is 35.895), we used the natural logarithm to account for the distribution of the variable.

5.5.2 Independent Variables

Corruption. Is measured based on the Corruption perceptions index (CPI) annually provided by Transparency International since 1995[85]. It relies on the informed views of analysts, business people and experts worldwide, e.g. expert assessment and opinion surveys and is currently reported for 176 countries.[86] A higher score means the country has less corruption. We used the reverse coding of this variable so that a higher score means more corruption to facilitate interpretation. The data is only available until 2016. We followed earlier cross-cultural studies (e.g., Roulet and Touboul, 2015) and predicted the value for 2017 based on a linear prediction of the previous years. Again, for Europe we used the average score from the countries cited above.[87]

Institutional voids (emerging market). In order to categorize the markets into emerging markets and non-emerging while creating a dummy variable where 1 equals emerging markets, we used the category provided by the UNDP[88] provided by Development Policy and Analysis

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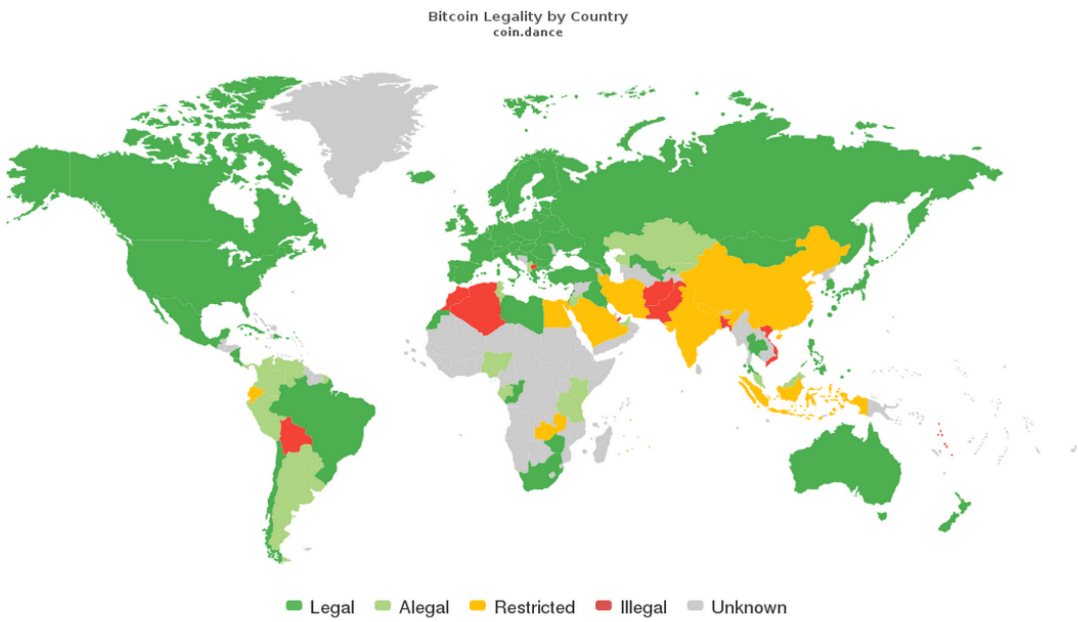
[85] www.transparency.org; Data is available from (http://files.transparency.org/content/download/2155/13635/file/CPI2016_FullDataSetWithRegionalTables.xlsx)
[86] https://www.transparency.org/research/cpi
[87] For corruption, the CPI is considered a robust measure and a stronger indicator than that of the World Bank (the CPIA), which strikes us as strongly underreporting corruption (e.g. the World Bank assigns a CPIA value of 2 for "relatively low" corruption to Afghanistan, known to be a country with historically high public sector corruption).
[88] http://www.un.org/en/development/desa/policy/wesp/wesp_current/2014wesp_country_classification.pdf

Division (DPAD) of the Department of Economic and Social Affairs of the United Nations Secretariat (UN/DESA).[89] We grouped the three transition countries Kazakhstan, Russia and Ukraine into the developed markets categories. However, grouping them into the emerging category does not change our results.

Institutional voids (level of institutional regulation). The level of institutional regulation was coded according to the level of regulation in a specific country in four categories (neutral; restricted; legal and illegal). The authors coded the categories independent of each other and obtained consistent results (over 97% of the cases were clear). For the remaining cases, mostly based on the timing of legal changes, the authors discussed the situation and came up with an agreement: if a country assigned a legal status, either illegal or legal, to bitcoin trading vs having no regulations in place (1=presence of a legal status). The coding was based on the coin Dance Website and press releases and was updated by each week. Figure 3 below provides an overview over the legal status of Bitcoins in each country in 2018.

[89] We used this categorization because it is based on various sources and information obtained from the Statistics Division and the Population Division of UN/DESA, as well as from the five United Nations regional commissions, the United Nations Conference on Trade and Development (UNCTAD), the United Nations World Tourism Organization (UNWTO), the International Monetary Fund (IMF), the World Bank, the Organization for Economic Cooperation and Development (OECD), and national and other private sources provided by the countries under investigation.

Figure 3: Bitcoin legality by country in 2018



Source: https://coin.dance/poli (as accessed on July 6th, 2018)

5.5.3 Control Variables

GDP per capita (current USS). We used the GDP per capita defined as the gross domestic product divided by midyear population provided by the World Bank as an indicator for economic prospects and growth. Data are in current U.S. dollars. We used a linear prediction for GDP per capita (current US$) for Venezuela based on the last five years (2010-2014) because data were only available until 2014.

Internet access (percent of population). We control for internet access because people can only participate in bitcoin trading if they have access to the internet. Internet users are individuals who have used the Internet via a computer, mobile phone, personal digital assistant, games machine, digital TV or others (from any location) in the last 3 months measured in percent of the population of a particular country. Again, we used the Data provided by the World Bank to measure this variable. The data is only available until 2016. Therefore, we used a linear prediction from the last available five years to predict the respective values for 2017.

Electricity access (percent of population). We again used the data from the World Bank as an indicator for access to electricity. We controlled for this variable because of small transaction costs and the marginal costs of mining. Again, this data is only available until 2016. Therefore, we used a linear prediction from the last available years to predict the values for 2017.

Population (ln). We further control for the number of people living in a country in a given year. Again, we used the data from the World Bank as indicator for population size. To normalize the distribution of this variable we used the natural log.

Number alternative cryptocurrencies. This is a count variable, where we counted the number of alternative cryptocurrencies available and active in a particular week. To measure this variable, we also studied several press releases and a list provided by Wikipedia[90]

Wallet users (ln). Wallets are data files that include Bitcoin accounts, recorded transactions, and private keys which are important to spend or transfer the stored value. Since many users rely on a digital wallet service that keeps the required files on a shared server with access via the web or via phone-based apps (Böhme et al. 2015: 221) we control for the number of wallet users in a particular country. We obtained data from the number of wallet users from the Blockchain platform. Blockchain is the world's leading (self-declared) software platform for digital assets[91] The software has powered over 100M transactions and empowered users in 140 countries across the globe to transact quickly and without costly intermediaries.

Inflation. We also control for the level of inflation (in percent) in a particular country in a particular year which impacts consumer prices.[92] We again used the data from the World Bank as indicator for inflation.

Financial stability. Financial Development Index. We used the data provided by the International Monetary Fund. The dataset contains nine indices that summarize how developed

[90] https://en.wikipedia.org/wiki/List_of_cryptocurrencies , as accessed on June 1st, 2018
[91] https://blockchain.info/charts/my-wallet-n-users
[92] Inflation as measured by the consumer price index reflects the annual percentage change in the cost to the average consumer of acquiring a basket of goods and services that may be fixed or changed at specified intervals, such as yearly.

financial institutions and financial markets are in terms of their depth, access and efficiency. These indices are aggregated into an overall index of financial development.

Year dummies. We included the year dummies to account for the general trends in the data over time.

Google bitcoin attention (ln). Search requests for the term „bitcoin" via Google trends[93]. Note that this data is relative. Google trends states "Numbers represent search interest relative to the highest point on the chart for the given region and time. A value of 100 is the peak popularity for the term. A value of 50 means that the term is half as popular. Likewise, a score of zero means the term was less than 1% as popular as the peak." To normalize the distribution of this variable we used the natural log.

Entry week on platform. The respective entry week for Bitcoin trading in a given country on our global trading platform (there are 208 weeks in our dataset, but some countries began trading later).

Homicides rate[94]. Intentional homicides rate (per 100,000 people) based the UN Office on Drugs and Crimes International Homicide Statistics database available via the World Bank[95]. Intentional homicides are estimates of unlawful homicides purposely inflicted as a result of domestic disputes, interpersonal violence, violent conflicts over land resources, intergang violence over turf or control, and predatory violence and killing by armed groups. Intentional homicide does not include all intentional killing; the difference is usually in the organization of the killing. Individuals or small groups usually commit homicide, whereas killing in armed conflict is usually committed by fairly cohesive groups of up to several hundred members and is thus usually excluded. For this variable, data were only available until 2015. We predicted the values for 2016 and 2017 based on the values available from 2011 until 2015. The average

[93] https://trends.google.com/trends/explore?q=bitcoin

[94] As corruption is a perceptive measure, we include the homicide rate as a hard indicator of corruption and criminality.

[95] https://data.worldbank.org/indicator/VC.IHR.PSRC.P5

mean of the standard deviation in this time span was .643 as the number is relatively stable over time for a particular country.

5.6 Model Specification

Since our data is in panel format, to decide whether the random or fixed effects model is the more appropriate regression model, we first ran the regression with random effects and then the alternative model with fixed effects, storing the respective estimates. We then ran the Hausman specification test to check the appropriateness of the random effects estimator. Hausman's test is based on estimating the variance *var(b-B)* of the difference of the estimators by the difference *var(b)-var(B)* of the respective variances. The test requires a sufficient sample size, a criterion which we clearly meet with our dataset of over 8000 observations per country (at the aggregated, weekly resolution). It also requires minimal asymptotic variance, which we believe is given since our observations are not weighted[96]. The Hausman test was insignificant (Chi^2=17, p>.05) thus supporting the null hypothesis that there is no correlation between the unique errors and the regressions in the model and that the random effects model is more efficient. In addition, as Allison (2009: 3) notes "If predictor variables vary greatly across individuals but have little variation over time for each individual, then fixed effects estimates will be very imprecise". While random effects (panel) models allow us to adjust for unobserved time-invariant confounders, as a robustness test, we nonetheless additionally report the alternative model with fixed effects (see the robustness check and the Appendix).

[96] For further details, please see the Stata Manual for the *hausman* command or any good econometrics textbook.

5.7 Results

Table 1 shows our correlation table and the descriptive results. The figure below depicts the bitcoin trading volume over time in each nation in our dataset. First, we find that as expected, bitcoin trading has experienced phenomenal growth over the last five years in all countries observed: The platform clearly launched later in some countries than others. Simultaneously, growth patterns differ both in terms of scale and variance (distribution of trades). The countries with the overall highest trading volume are the US, UK, Russia, Australia, China and South Africa; countries with the lowest overall trading volume include Tanzania, Kazakhstan, Indonesia, Hungary, Japan, Vietnam, Denmark and the Dominican Republic.

Figure 4: Weekly Bitcoin Trading over Time by Country

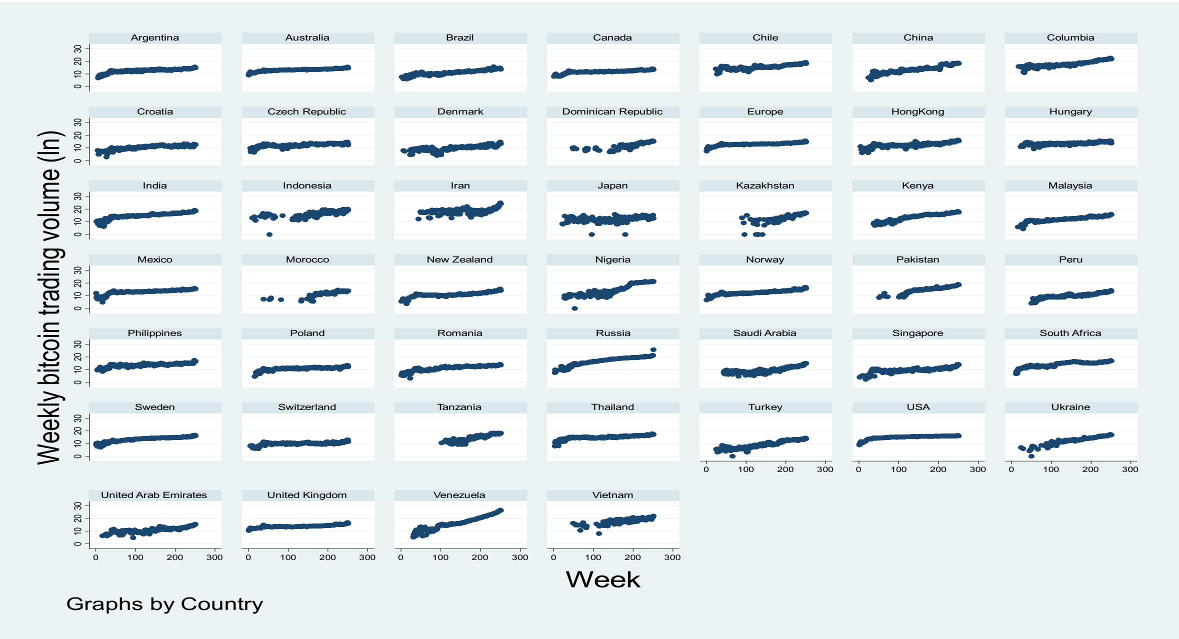


Table 1: Descriptive Statistics and Correlation Table

#	Variable	Mean	Std. Dev.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	Weekly bitcoin trading volume (ln)	13.054	3.069																			
2	GDP per capita	24,143.320	23,502.040	-0.3884																		
3	Internet access (percent)	64.689	22.172	-0.3280	0.7754																	
4	Electricity access (percent)	95.595	13.315	-0.1768	0.3423	0.5461																
5	Population (ln)	17.464	1.409	0.3707	-0.5351	-0.6637	-0.3279															
6	Number alternative cryptocurrencies	27.751	13.643	0.4765	-0.1226	0.0461	-0.0146	0.0356														
7	Wallet users (ln)	15.255	1.115	0.5102	-0.1277	0.0478	-0.0159	0.0237	0.9290													
8	Inflation	5.088	10.353	0.2389	-0.2400	-0.2046	-0.0598	0.0857	0.0069	0.0426												
9	Financial stability	0.535	0.215	-0.2943	0.8003	0.6010	0.3293	-0.1994	-0.0992	-0.1125	-0.3976											
10	Year	2015.322	1.313	0.4944	-0.1240	0.0466	-0.0217	0.0289	0.9857	0.9621	0.0311	-0.1074										
11	Region	4.553	2.933	0.1644	-0.3801	-0.5298	-0.3427	0.1780	0.0721	0.0697	0.1061	-0.4552	0.0746									
12	Google bitcoin attention (ln)	1.213	0.826	0.2848	0.0982	0.0834	-0.1099	-0.0851	0.4355	0.3958	-0.031	0.0173	0.4249	-0.0603								
13	Entry week on platform	15.632	19.593	0.1592	-0.3610	-0.1632	-0.0670	0.0284	0.1834	0.1957	0.2973	-0.4322	0.191	0.0622	0.0134							
14	Homicides rate	7.000	11.475	0.3308	-0.4014	-0.3401	-0.1609	0.1805	0.0002	0.0274	0.6694	-0.4051	0.0137	0.0395	-0.1003	0.1861						
15	Corruption	46.360	22.299	0.4651	-0.8934	-0.7782	-0.3002	0.5640	0.0964	0.1086	0.4372	-0.7932	0.1036	0.3937	-0.1282	0.4227	0.5583					
16	Legal status neutral	0.354	0.478	0.2589	-0.3565	-0.3327	-0.2334	0.1197	-0.1013	-0.0837	0.329	-0.5573	-0.0961	0.284	-0.0470	0.2512	0.2809	0.4357				
17	Legal status restricted	0.045	0.207	0.2222	-0.1387	-0.1479	0.0434	0.1269	0.2009	0.1752	0.023	-0.1506	0.1959	0.0764	0.1411	0.1262	-0.0943	0.1354	-0.1137			
18	Legal status legal	0.556	0.497	-0.3599	0.4841	0.4224	0.1626	-0.3005	0.0577	0.0527	-0.3163	0.6147	0.0588	-0.2684	0.0534	-0.3101	-0.2094	-0.5833	-0.8029	-0.2358		
19	Legal status illegal	0.045	0.208	0.0771	-0.2044	-0.1191	0.0748	0.2838	-0.0737	-0.0776	0.0063	-0.086	-0.082	-0.0448	-0.1218	0.0621	-0.0324	0.2580	-0.1624	-0.0477	-0.3369	
20	Emerging market (=1)	0.578	0.494	0.1294	-0.3984	-0.6565	-0.3060	0.2698	0.0532	0.0638	0.2403	-0.326	0.06	0.3895	-0.0428	0.0649	0.4013	0.5165	0.1736	0.0674	-0.1798	-0.0112

(obs=8,062)

We test the hypothesized effects based on Table 2 Model 6. Several robustness checks showed a highly consistent picture for the main effects in models without interaction terms (see also the fixed effects models in the Appendix). In the additional analysis we investigate in greater detail how the level of institutional regulation impacts bitcoin trading. First, in H1 we stated that a strong legal regulation will be negatively related with Bitcoin trading volume over time. We find (Table 2, Model 6) that the coefficient of the level of regulation in a country has a negative and significant impact on the trading volume in a particular country (ß=-0.135, $p<.05$).

Second, in our second hypothesis (H2), we assumed that emerging markets have a higher bitcoin trading than non-emerging markets. We find that in Model 5 (Table 2) the country's emerging market status is significantly positively related with Bitcoin trading volume over time (ß=1.806, $p<.05$). Thus, we can support H2. However, in Model 6 (Table 2) with the interaction terms, this positive main relationship turns negative and is slightly significant (ß=-2.519, $p<.05$).

In H3 we hypothesized that the level of perceived corruption would be significantly positively related with Bitcoin trading volume over time. However, contrary to H3, we find (Table 2, Model 6) that the coefficient of the level of perceived corruption in a country has a negative and significant impact on the trading volume in a particular country (ß=-0.081, $p<.001$).

Next, in H4, we stated that a strong legal regulation of bitcoin trading will negatively moderate the relationship between corruption and the level of Bitcoin trading over time: The coefficient for the interaction term between corruption and a strong legal status is indeed negatively significant (ß=-0.005, $p<.001$), supporting our H4.

Finally, we assumed in H5 that a country's emerging market status positively moderates the relationship between corruption and the level of Bitcoin trading over time. In Model 6 (Table 2) the coefficient for the interaction term is significant and positive (ß= 0.107, $p<.001$), supporting our hypothesis H5.

Table 2: Random-effects GLS Panel regression (DV: Bitcoin Trading by Country)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Emerging market (=1)			1.789*		1.806*	-2.519*
			(0.808)		(0.750)	(1.069)
Legal status regulation				-0.368***	-0.361***	-0.135**
				(0.023)	(0.023)	(0.051)
Corruption		-0.049***			-0.041***	-0.081***
		(0.010)			(0.010)	(0.014)
Corruption x Legal status regulation						-0.005***
						(0.001)
Corruption x emerging market						0.107***
						(0.018)
GDP per capita	-0.000*	-0.000**	-0.000*	-0.000*	-0.000**	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Internet access (percent)	0.017*	0.021**	0.020*	0.033***	0.039***	0.051***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Electricity access (percent)	0.126***	0.122***	0.127***	0.113***	0.111***	0.115***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Population (ln)	1.023***	1.383***	0.862***	1.083***	1.224***	1.125***
	(0.247)	(0.261)	(0.260)	(0.227)	(0.248)	(0.251)
Number alternative cryptocurrencies	-0.039***	-0.040***	-0.040***	-0.038***	-0.039***	-0.043***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Wallet users (ln)	1.499***	1.489***	1.500***	1.511***	1.504***	1.507***
	(0.057)	(0.056)	(0.056)	(0.056)	(0.056)	(0.055)
Inflation	-0.042***	-0.041***	-0.042***	-0.041***	-0.041***	-0.042***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Financial stability	-5.139***	-6.783***	-4.964***	-7.052***	-8.280***	-7.283***
	(0.977)	(1.034)	(0.983)	(0.956)	(1.014)	(1.020)
Year dummies	included	included	included	included	included	included
Google bitcoin attention (ln)	0.673***	0.678***	0.672***	0.659***	0.663***	0.668***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Entry week on platform	0.024	0.036*	0.017	0.004	0.007	0.013
	(0.016)	(0.016)	(0.016)	(0.014)	(0.015)	(0.015)
Homicides rate	-0.148***	-0.152***	-0.156***	-0.139***	-0.149***	-0.151***
	(0.017)	(0.018)	(0.018)	(0.017)	(0.017)	(0.017)
Constant	-36.293***	-39.190***	-34.764***	-35.042***	-35.939***	-35.074***
Chi2	14681.456	14759.327	14701.297	15333.982	15405.27	15587.211
N	8,062	8,062	8,062	8,062	8,062	8,062

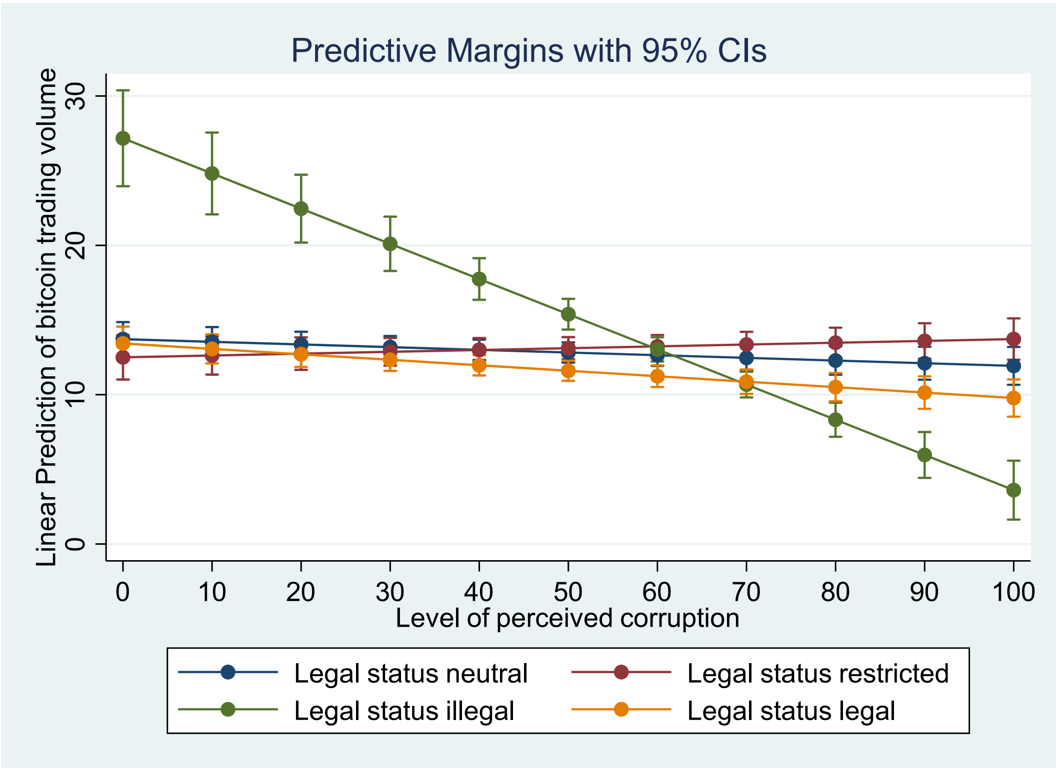
Legend: † p<.1; * p<.05; ** p<.01; *** p<.001

Next, we report the results of our control variables again based on Table 2, Model 6. First, we see that GPD per capita is negative and significant but the overall effect is very small (ß=-0.000, p<.001). Second, we find that the percent of population with internet access in a given country is positively significant (ß=0.051, p<.001). The same is the case for access to electricity (ß=0.115, p<.001) and the natural log of population (ß=0.125, p<.001). The number of alternative cryptocurrencies in the market at a given point in time is negatively significantly related to trading volume (ß=-0.043, p<.001). The natural log of the number of wallet users is significantly positively related to the level of bitcoin trading over time (ß=1.507, p<001). Further, we find that inflation (ß=-0.042, p<.001) and financial stability (ß=-7.283, p<.001) in a given country is significantly negatively related to bitcoin trading volume over time. Next, we find that Google attention to Bitcoin (the natural log of the quantity of Google searches for "Bitcoin" in each country) is significantly positively related to trading volume (ß=0.668, p<.001). While entry week (the week a country began trading on our platform) is positive but not significantly related to trading (ß=0.013, n.s.). The homicides rate in a given country is significantly negatively related to Bitcoin trading volume (ß=-0.151, p<.001).

5.8 Additional Analysis

To investigate our hypothesis in greater detail we conducted two additional analysis. First, we investigated H5 in greater detail and in this sense the question how the level of institutional regulation impacts bitcoin trading over time, we split the level of institutional regulation in the different categories (i.e., neutral, regulated, legal and illegal). Table 3 Model 10 shows the coefficients for the interaction between corruption and legal status. We find that the interaction between corruption and legal status restricted is significant and positive (ß=0.03, p<.05), the interaction term between corruption and legal status legal is indeed negatively significant (ß=-0.218, p<.001) and the interaction term between corruption and legal status illegal is in the model with only one interaction (Model 8) highly significant negative but in the full model (Model 10) only slightly significant negative (ß=-0.289†, p<.1). These results strengthen our hypotheses that a greater institutional regulation (i.e., declaring bitcoin trading as either legal or illegal) has a negative impact on bitcoin trading. A graphical illustration of these results is displayed below (Figure 5). Figure 5 illustrates the strong moderation effect of corruption on the relationship between legal status illegal and bitcoin trading. The higher the level of perceived corruption the lower the bitcoin trading volume if trading is declared as illegal.

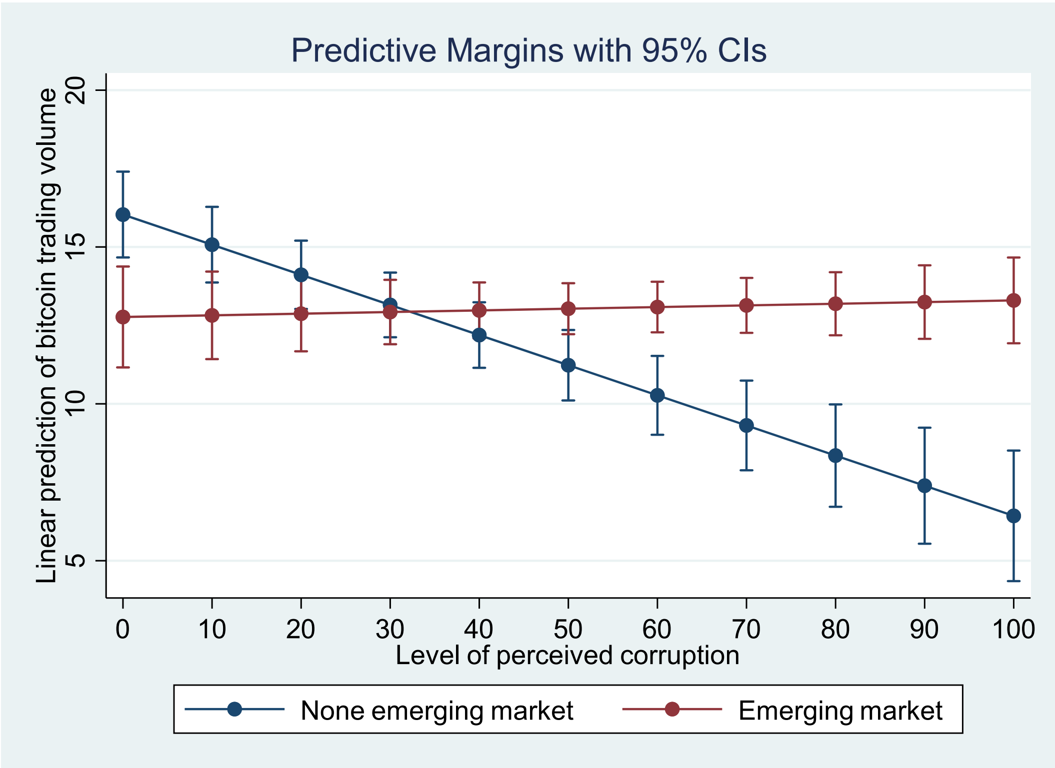
Figure 5: Interaction between level of institutional regulation and corruption



Note: Figure is based on Model 10 in Table 3.

Figure 6 displays the interaction between emerging market and corruption. Figure 6 shows how corruption impacts emerging and non-emerging markets differently.

Figure 6: Interaction between Emerging Market Status and Corruption



Note: Figure is based on Model 10 in Table 3.

Second, we investigated in greater detail the regions in which bitcoin trading has the strongest impact beyond the dichotomous categorization of emerging market and non-emerging market (Table 4, Model 6). We study nine different geo-cultural regions with the Anglo-America region serving as a base category. We used the region categories from the GLOBE study (House et al, 2004) and the regions are Confucian Asia region, Eastern Europe region, Latin Europe region, Middle East, Nordic Europe, Southern Asia Sub-Sahara Africa region. We find that, compared to Anglo-America, the Confucian Asia as well as Middle east region (ß=-0.063, n.s.) is negatively but not significant related to trading volume. The coefficients for Eastern Europe (ß=-1.234, p<.001), Latin Europe (ß=-2.397, p<.001) and Latin America (ß=-1.939, p<.001) are significant and negative. However, Southern Asia (ß=1.286, p<.001) and Sub-Saharan Africa (ß=2.045, p<.001) are significantly positively related to Bitcoin trading volume.

Table 3: Random-effects GLS Panel regression (DV: Bitcoin Trading by Country) with interaction categories

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Emerging market (=1)			1.789*		1.693*	1.536*	1.484†	1.904*	-2.093†	-2.189*
			(0.808)		(0.777)	(0.730)	(0.782)	(0.759)	(1.102)	(1.073)
Legal status restricted (Base: Status neutral)				0.466***	0.445***	-1.493*	0.697***	0.432***	0.370***	-1.218*
				(0.103)	(0.103)	(0.595)	(0.106)	(0.103)	(0.104)	(0.592)
Legal status Illegal (Base: Status neutral)				-0.801***	-0.796***	-0.802***	13.486***	-0.870***	-0.841***	13.448***
				(0.111)	(0.111)	(0.111)	(1.584)	(0.111)	(0.111)	(1.578)
Legal status legal (Base: Status neutral)				-1.103***	-1.081***	-1.090***	-1.021***	-0.268†	-1.119***	-0.289†
				(0.073)	(0.073)	(0.073)	(0.073)	(0.156)	(0.074)	(0.156)
Corruption		-0.049***			-0.037***	-0.042***	-0.029**	-0.024*	-0.087***	-0.070***
		(0.010)			(0.010)	(0.010)	(0.010)	(0.010)	(0.014)	(0.014)
Corruption x Legal status restricted						0.032***				0.030**
						(0.010)				(0.010)
Corruption x Legal status Illegal							-0.216***			-0.218***
							(0.024)			(0.024)
Corruption x Legal status legal								-0.020***		-0.019***
								(0.003)		(0.003)
Corruption x emerging market									0.090***	0.091***
									(0.018)	(0.018)
GDP per capita	-0.000*	-0.000**	-0.000*	-0.000**	-0.000***	-0.000**	-0.000**	-0.000***	-0.000***	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Internet access (percent)	0.017*	0.021**	0.020*	0.031***	0.036***	0.030***	0.033***	0.052***	0.035***	0.044***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)
Electricity access (percent)	0.126***	0.122***	0.127***	0.115***	0.114***	0.111***	0.118***	0.110***	0.119***	0.119***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Population (ln)	1.023***	1.383***	0.862***	1.051***	1.174***	1.184***	1.128***	1.289***	1.015***	1.081***
	(0.247)	(0.261)	(0.260)	(0.233)	(0.256)	(0.241)	(0.258)	(0.251)	(0.261)	(0.252)
Number alternative cryptocurrencies	-0.039***	-0.040***	-0.040***	-0.039***	-0.040***	-0.040***	-0.040***	-0.044***	-0.041***	-0.043***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Wallet users (ln)	1.499***	1.489***	1.500***	1.510***	1.503***	1.501***	1.486***	1.507***	1.504***	1.489***
	(0.057)	(0.056)	(0.056)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)
Inflation	-0.042***	-0.041***	-0.042***	-0.043***	-0.042***	-0.042***	-0.043***	-0.043***	-0.042***	-0.044***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Financial stability	-5.139***	-6.783***	-4.964***	-6.753***	-7.871***	-7.950***	-7.933***	-7.290***	-7.370***	-6.996***
	(0.977)	(1.034)	(0.983)	(0.961)	(1.020)	(1.011)	(1.017)	(1.019)	(1.026)	(1.019)
Year dummies	included	included	included	included	included	included	included	Included	Included	included
Google bitcoin attention (ln)	0.673***	0.678***	0.672***	0.668***	0.671***	0.674***	0.696***	0.676***	0.671***	0.704***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Entry week on platform	0.024	0.036*	0.017	0.003	0.006	0.005	0.003	0.010	0.009	0.010
	(0.016)	(0.016)	(0.016)	(0.015)	(0.016)	(0.015)	(0.016)	(0.015)	(0.016)	(0.015)
Homicides rate	-0.148***	-0.152***	-0.156***	-0.138***	-0.148***	-0.135***	-0.149***	-0.139***	-0.154***	-0.140***
	(0.017)	(0.018)	(0.018)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Constant	-36.293***	-39.190***	-34.764***	-35.038***	-35.810***	-35.150***	-35.355***	-39.766***	-32.210***	-34.907***
Chi2	14681.456	14759.327	14701.297	15562.855	15626.767	15616.353	15872.5	15712.733	15705.096	16054.244
N	8,062	8,062	8,062	8,062	8,062	8,062	8,062	8,062	8,062	8,062

Legend: † p<.1; * p<.05; ** p<.01; *** p<.001

Table 4: Random-effects GLS Panel regression (DV: Bitcoin Trading by Country) with regions

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Emerging market (=1)			2.950**		3.103***	-1.449***
			(0.975)		(0.878)	(0.274)
Legal status restricted (Base: Status neutral)				0.451***	0.434***	-5.748***
				(0.119)	(0.119)	(0.789)
Legal status Illegal (Base: Status neutral)				-0.865***	-0.863***	0.653
				(0.118)	(0.118)	(1.895)
Legal status legal (Base: Status neutral)				-1.063***	-1.081***	1.452***
				(0.083)	(0.082)	(0.183)
Corruption		-0.066***			-0.035**	0.182***
		(0.013)			(0.012)	(0.006)
Corruption x Legal status restricted						0.112***
						(0.013)
Corruption x Legal status Illegal						-0.043
						(0.029)
Corruption x Legal status legal						-0.075***
						(0.003)
Corruption x emerging market						-0.016*
						(0.006)
GDP per capita	-0.000**	-0.000**	-0.000**	-0.000***	-0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Internet access (percent)	0.004	0.011	0.003	0.016†	0.021*	-0.001
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.005)
Electricity access (percent)	0.289***	0.281***	0.277***	0.232***	0.229***	0.053***
	(0.030)	(0.031)	(0.030)	(0.030)	(0.029)	(0.011)
Population (ln)	0.601*	0.964**	0.706***	0.586*	0.848***	-0.112**
	(0.299)	(0.328)	(0.209)	(0.237)	(0.198)	(0.040)
Number alternative cryptocurrencies	-0.037***	-0.039***	-0.036***	-0.037***	-0.038***	-0.031***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
Wallet users (ln)	1.440***	1.432***	1.435***	1.451***	1.445***	1.426***
	(0.066)	(0.066)	(0.067)	(0.065)	(0.065)	(0.084)
Inflation	-0.042***	-0.041***	-0.042***	-0.044***	-0.043***	-0.066***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Financial stability	-4.691**	-7.711***	-4.467**	-5.040***	-5.771***	5.227***
	(1.588)	(1.713)	(1.419)	(1.489)	(1.452)	(0.343)
Year dummies	Included	Included	Included	Included	Included	Included
Confucian Asia region (Base: Anglo America region)	-4.026**	-4.031**	-5.322***	-3.470***	-4.943***	-0.146
	(1.287)	(1.375)	(1.086)	(1.015)	(0.966)	(0.146)
Eastern Europe region (Base: Anglo America region)	-4.131**	-3.514*	-3.142**	-4.043***	-2.674**	-1.234***
	(1.525)	(1.630)	(1.079)	(1.217)	(0.970)	(0.174)
Latin Europe region (Base: Anglo America region)	-3.634*	-3.196†	-4.094***	-3.542**	-3.880***	-2.397***
	(1.647)	(1.763)	(1.183)	(1.297)	(1.046)	(0.143)
Latin America region (Base: Anglo America region)	1.886	3.630*	-1.458	0.365	-1.850†	-1.939***
	(1.347)	(1.459)	(1.238)	(1.102)	(1.115)	(0.194)
Middle East region (Base: Anglo America region)	-4.719**	-3.835*	-6.639***	-4.576***	-6.099***	-0.063

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	(1.669)	(1.788)	(1.467)	(1.332)	(1.308)	(0.201)
Nordic Europe region (Base: Anglo America region)	-2.365	-3.070†	-1.366	-2.094	-1.542	0.175
	(1.659)	(1.777)	(1.150)	(1.305)	(1.015)	(0.109)
Southern Asia region (Base: Anglo America region)	-0.504	0.560	-2.933*	-1.092	-2.769*	1.286***
	(1.454)	(1.557)	(1.323)	(1.180)	(1.182)	(0.166)
Sub-Sahara Africa region (Base: Anglo America region)	10.152***	10.732***	7.191***	7.099**	5.235**	2.045***
	(2.652)	(2.789)	(2.113)	(2.231)	(1.928)	(0.450)
Google bitcoin attention (ln)	0.646***	0.653***	0.650***	0.653***	0.656***	0.715***
	(0.033)	(0.033)	(0.033)	(0.032)	(0.032)	(0.038)
Entry week on platform	0.037	0.055*	0.030†	0.017	0.023	-0.040***
	(0.026)	(0.028)	(0.018)	(0.020)	(0.016)	(0.003)
Homicides rate	-0.170***	-0.185***	-0.119***	-0.123***	-0.088***	0.105***
	(0.020)	(0.020)	(0.018)	(0.019)	(0.017)	(0.005)
Constant	- 41.322***	- 43.155***	- 42.961***	- 35.267***	- 39.073***	- 20.755***
Chi2	9895.3434	9984.1109	9763.3687	10479.386	10408.579	15632.25 1
N	6,068	6,068	6,068	6,068	6,068	6,068

Legend: † p<.1; * p<.05; ** p<.01; *** p<.001

The table below summarizes our hypothesized effects and findings (Table 5):

Table 5: Summary of Hypothesized Effects and Findings

#	Hypothesis	Type	Finding
H1	Strong legal regulation will be negatively related with Bitcoin trading volume over time.	Direct effect (-)	Supported (-)
H2	The country's emerging market status will be positively related with Bitcoin trading volume over time.	Direct effect (+)	Supported (+)
H3	The level of perceived corruption in a country is positively related to the country's Bitcoin trading volume over time.	Direct effect (+)	Contrary (-)
H4	Corruption will negatively moderate the relationship between strong legal regulation and the level of Bitcoin trading over time.	Interaction (-)	Supported (-)
H5	The country's emerging market status will positively moderate the relationship between corruption and the level of Bitcoin trading over time.	Interaction (+)	Supported (+)

5.9 Robustness Checks

To rule out spurious effects due to misspecification of our variables and model specifications, we re-run our model with a fixed effect regression and our results stay the same (Table 6, Appendix). However, in this regression we lose two variables (entry week and emerging market category) due to their time invariant nature.

To further underscore the robustness of our data, we ran the same model again with an alternate operationalization of our dependent variable. First, we used a relative measure - the Trading Volume (per country over time) divided by the GDP per capita (per country over time) with similar results. Finally, to see how well our model explains Bitcoin awareness, we ran an additional model with Google Awareness (search results for "Bitcoin") as the dependent variable.

5.10 Discussion

Our finding that strong legal regulation is negatively related with Bitcoin trading volume over time (**H1**) is in line with our theoretical expectations. First, clearly a ban in a given country would significantly hamper trading. This would also be a questionable tactic for governments as it would force certain traders into the criminal space or to use alternative services, if available, that are likely to be much less transparent than the publicly available general transaction ledger underlying Bitcoin trade. Consider for example, how banning the sale of Marihuana forces sellers into illegal territory with no possibility for the government to control quality or to benefit from potentially sizeable sales tax revenues, both driving forces behind the recent legalization movement in the US. Similarly, history has shown that the prohibition of alcohol sales initially drives up the price but ultimately leads to the growth and legitimation of urban crime organizations (e.g. in the US in the 1920s). Strong legal regulation in place of a ban, would also extinguish innovation in this bustling new sector and would make trading less attractive.

Second, our finding that country's emerging market status is positively related with Bitcoin trading volume (**H2**) supports our contention that emerging markets are using Bitcoins to leapfrog over outdated technologies (e.g. Fudenberg, Stiglitz & Tirole, 1983) in order to catch up with advanced countries. In addition, in some countries such as Venezuela, Bitcoins seem to be used for survival motives, acting as a substitute (store of value) for hyperinflated local currencies. Our finding also supports our expectation that in advanced countries, Bitcoin trading is more of a luxury (speculative, high-risk investment activity).

Our finding that the level of perceived corruption in a country is negatively related to the country's Bitcoin trading volume over time (contradicting **H3**) is surprising as it is most commonly assumed that such trading is used to launder illicit economic activity and for tax evasion. One explanation for this could be that cryptocurrency transactions can play a role in closing perceived trust gaps (e.g. information asymmetry) between transaction partners, as such transactions are publicly recorded in a global digital ledger, requiring little or no intermediation.

Next, we discuss our findings on the hypothesized interactions. First, our finding that the perceived level of corruption negatively moderates the relationship between strong legal regulation and the level of bitcoin trading over time as predicted (**H4**), makes intuitive sense: where strong legal legislation is in place (e.g. considerable trading restrictions or an outright ban), a high level of (perceived) corruption would imply that the legislation would have less effect on trading volume. Where people are willing to bend the rules, they are more likely to ignore laws. Lastly, our finding that the country's emerging market status positively moderates the relationship between corruption and the level of bitcoin trading over time is in line with our theoretical expectations (**H5**): Our results here again support the leapfrogging hypothesis (e.g. Fudenberg, Stiglitz & Tirole, 1983) but also indicate the role of institutional voids as contingencies (e.g. Khanna and Palepu, 1997). Corruption seems to play a stronger role in emerging than in developed countries, where strong institutions can act as a buffer to mitigate the effects of corruption. In emerging markets, Bitcoin trading may also serve as a method to circumvent unnecessary interaction with corrupt government officials.

These results have both theoretical (e.g. for research streams that juxtapose innovation, institutional voids, corruption and trust) and practical implications (e.g. for cryptopreneurs[97], institutional entrepreneurs and policy-makers. From a practical perspective, effective innovation policies for cryptocurrencies will require regulators to walk a fine line between sanction mechanisms and enforcement, on the one hand, and incentive structures on the other: while preventing largescale fraud and tax evasion is of course necessary, this should be implemented without choking a rapidly emerging and innovative market with the potential for job-creation and for revitalizing often volatile economies. Also, since cryptopreneurs are particularly active in emerging countries, this could be a sign that governments in such countries see the (decentralized) crypto-space as a potential mechanism to help them catch up with more highly developed countries by means of leapfrogging (e.g. Fudenberg, Stiglitz & Tirole, 1983) and mastering the digital transformation. If so, this would lead to a purposefully low degree of regulation in such markets, in line with the view of transaction cost economics (e.g. North & North, 1992; Williamson, 1979). North argues that lower transaction costs –the costs of trade– lead to economic growth and that institutions play a key role in either raising or lowering transaction costs (North, 1992).

In an interview with a blogger Russ Roberts in September 2006, Nobel Laureate Milton Friedman suggests that the money supply should be controlled not by human beings with often

[97] We use the term *cryptopreneurs* to refer to entrepreneurs in the cryptocurrency space, who inspired this study.

misaligned incentive structures, but by a computer program: "Roberts: But the alternative, the elected system, has the problem that you mentioned earlier of the temptation to exploit the ability to create money to increase revenue. Friedman (replies): But that's why what you want—if possible—is a mechanical system." [98] In the discussion that follows, Friedman later remarks: "If you really carried out the logic concerning the quantity of money, you deprive the Federal Reserve of anything to do. Suppose the Federal Reserve said it was going to increase the quantity of money by 4 percent a year, year after year, week after week, month after month. That would be a purely mechanical project. You could program a computer to do that." A mere three years later, a person with the alias Satoshi Nakamoto created the Bitcoin algorithm, the first truly decentralized currency. Recently we even witnessed the situation were Venezuelan President Maduro stated he would peg the local currency to the state-initiated and monitored cryptocurrency, "Petro" (named after the country's considerable oil supply) – a desperate move to attempt to temper hyperinflation in the country. Our findings imply that, while without any regulation society could be harmed, regulation can be detrimental if those in charge of regulating are not highly competent. In early phases of a new market, public discourse is therefore highly important to the healthy growth of a new market and to balancing the needs of society with those of entrepreneurs and early adopters.

If Bitcoins are not primarily traded for illicit but for legal reasons as our exploratory study implies (both the perception of high corruption in a country and the actual homicide rate are negatively related to overall trading volume), cryptocurrencies could pave the way for just such a system, earlier than most people –Nobel Laureates aside– anticipated. For entrepreneurs, our findings imply that in early phases of a new market, it can be a good strategy to stay under the radar, particularly in countries with high perceived levels of corruption.

We also believe that the results have implications for other contested markets linked to digital innovation (e.g. peer-to-peer vs. classical lending or the emergence of crowdfunding vs.

[98] http://www.econlib.org/library/Columns/y2006/Friedmantranscript.html

traditional venture capital). In conclusion, we want to emphasize that our paper examines surprising new market developments and finds interesting results worth further study that link to the conference theme.

5.11 Limitations and Future Research

Our study has a number of limitations. First, our measure of corruption (the CPI), is a perceptive measure. Hazards of governance indexes are well documented and some authors criticize governance assessment, mostly on methodological grounds (e.g. Arndt & Oman, 2006). Self-reported measures rely on the accounts of others, which may have incentives for misrepresentation. However, as this is the case for all countries in which the respective indicator is compiled, cross-national differences should nonetheless remain highly informative.

In addition, some authors have suggested that measurement bias can be a concern with government indexes (e.g. Olken, 2009). For instance, Olken (2009) suggest that countries added to the index very recently may be discriminated in the CPI due to perceptive biases spread by the media. Since our analysis observes only a subset of 43 countries available on the chosen trading platform which have all been part of the index for a considerable number of years, we believe that we can rule out this type of measurement bias for our analysis. Further, while it is arguably more direct to survey traders on the chosen online platform about their perceptions of corruption, this would be time and cost prohibitive (e.g. due to the number of countries and necessary translators involved). Also, fine-grained data on corruption are notoriously difficult to obtain and are often available only for few countries and a limited number of years (Fréchette, 2006).

Further research could include event history analysis or other multi-method approaches (e.g. combining qualitative findings with our or an alternative quantitative approach). In addition, further cross-societal comparisons and survey measures could elucidate counter-intuitive findings such as in this study and would be informative in shaping future research and policy to support entrepreneurship in newly contested digital markets.

Finally, while our model focuses on corruption and institutional voids, future studies could also study how the role of trust shapes the market for bitcoin trading. That is, how does the level of generalized societal trust impact trading volume overall and differently in emerging vs. developed countries? What about the role of institutions and trust in innovative new technologies? These are some of the questions we seek to explore with an ongoing global survey on the trust in and the perception of Bitcoins and cryptocurrencies worldwide.

5.12 References (Fourth empirical study)

Aldrich, H. E., & Fiol, C. M. (1994). Fools rush in? The institutional context of industry creation. *Academy of Management Review*, *19*(4), 645-670.

Allison, P. D. (2009). Fixed Effects Regression Models SAGE Thousand Oaks.

Anokhin, S., & Schulze, W. S. (2009). Entrepreneurship, innovation, and corruption. *Journal of Business Venturing*, *24*(5), 465-476.

Bariviera, A. F. (2017). The inefficiency of Bitcoin revisited: a dynamic approach. *Economics Letters*, *161*, 1-4.

Becker, G.S. (1968). Crime and Punishment: An Economic Approach. *Journal of Political Economy*, 76, 169-217.

Bertrand, M., Djankov, S., Hanna, R., & Mullainathan, S. (2007). Obtaining a driver's license in India: an experimental approach to studying corruption. *The Quarterly Journal of Economics*, *122*(4), 1639-1676.

Blundo, G., de-Sardan, J. P. O., Arifari, N. B., & Alou, M. T. (2013). *Everyday corruption and the state: Citizens and public officials in Africa*. Zed Books Ltd.

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., & Hagfors, L. I. (2017). On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier? *Finance Research Letters*, *20*, 192-198.

Bouri, E., Gupta, R., Tiwari, A. K., & Roubaud, D. (2017). Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. *Finance Research Letters*.

Böhme, R., Christin, N., Edelman, B., & Moore, T. (2015). Bitcoin: Economics, technology, and governance. *Journal of Economic Perspectives*, *29*(2), 213-38.

Child, J. (2001). Trust—the fundamental bond in global collaboration. *Organizational Dynamics,* 29(4), 274-288.

Christin, N. (2013). Traveling the Silk Road: A measurement analysis of a large anonymous online marketplace. In *Proceedings of the 22nd international conference on World Wide Web* (pp. 213-224). ACM.

Cumming, D. J., & Vismara, S. (2017). De-segmenting research in entrepreneurial finance. *Venture Capital*, *19*(1-2), 17-27.

Davidson, D.K. (2003): *Selling Sin: The Marketing of Socially Unacceptable Products* (2nd ed.). Westport: Praeger Publishers.

Del Monte, A., & Papagni, E. (2007). The determinants of corruption in Italy: Regional panel data analysis. *European Journal of Political Economy*, *23*(2), 379-396.

Dodd, N. (2017). The social life of Bitcoin. *Theory, Culture & Society*. DOI: 10.1177/0263276417746464

Dodgson, M., Gann, D., Wladawsky-Berger, I., Sultan, N., & George, G. (2015). Managing digital money. *Academy of Management Journal*, *58*(2), 325-333.

Durand, R., & Vergne, J. P. (2015). Asset divestment as a response to media attacks in stigmatized industries. *Strategic Management Journal*, *36*(8), 1205-1223.

Eckhardt, J. T., & Shane, S. A. (2003). Opportunities and entrepreneurship. *Journal of Management*, *29*(3), 333-349

Frechette, G. R. (2006). Panel data analysis of the time-varying determinants of corruption.

Fukuyama, F. (1995). Trust: The Social Virtues and the Creation of Prosperity. New York: Free Press.

Gao, C., Zuzul, T., Jones, G., & Khanna, T. (2017). Overcoming institutional voids: A reputation-based view of long-run survival. *Strategic Management Journal*, 38, 2147-2167.

Georgallis, P., Dowell, G., & Durand, R. (2018). Shine on Me: Industry Coherence and Policy Support for Emerging Industries. *Administrative Science Quarterly*, 0001839218771550.

Geroski, P. (2003): *The Evolution of New Markets*. Oxford: Oxford University Press.

Navis, C., & Glynn, M. A. (2010). How new market categories emerge: Temporal dynamics of legitimacy, identity, and entrepreneurship in satellite radio, 1990–2005. *Administrative Science Quarterly*, *55*(3), 439-471.

House, R.J. et al. (2004), Culture, Leadership, and Organizations: The GLOBE Study of 62 Societies, Sage Publications.

Kaufmann, D., Kraay, A., & Mastruzzi, M. (2009). The worldwide governance indicators: Methodology and analytical issues. World bank policy research working paper No. 5430.

Khanna, T., & Palepu, K. 1997. Why focused strategies may be wrong for emerging markets. *Harvard Business Review*, 75(4): 41–51.

Khanna, T., Palepu, K., 2000. The future of business groups in emerging markets: long-run evidence from Chile. *Academy of Management Journal* 43 (3), 268–285.

Khanna, T., Rivkin, J.W., 2001. Estimating the performance effects of business groups in emerging markets. *Strategic Management Journal* 22 (1), 45–74.

Kwok, C. C. Y. & Tadesse, S. (2006). The MNC as an Agent of Change for Host-Country Institutions: FDI and Corruption, *Journal of International Business Studies*, 37 (6), 767-785

Kwong, J. (2015). *The political economy of corruption in China*. Routledge.

Lukes, S. (2004): *Power: A Radical View* (2nd edition). London: Palgrave MacMillan.

Maguire, S., Hardy, C., & Lawrence, T. B. (2004). Institutional entrepreneurship in emerging fields: HIV/AIDS treatment advocacy in Canada. *Academy of management journal*, *47*(5), 657-679.

Mair, J., & Marti, I. (2009). Entrepreneurship in and around institutional voids: A case study from Bangladesh. *Journal of Business Venturing*, 24(5), 419-435.

Mair, J., Martí, I., & Ventresca, M. J. (2012). Building inclusive markets in rural Bangladesh: How intermediaries work institutional voids. *Academy of Management Journal*, *55*(4), 819-850.

March, J. G. (1991). Exploration and exploitation in organizational learning. *Organization science*, *2*(1), 71-87.

Miller, D., Lee, J., Chang, S., & Le Breton-Miller, I. (2009). Filling the institutional void: The social behavior and performance of family vs non-family technology firms in emerging markets. *Journal of International Business Studies*, *40*(5), 802-817.

Mohanty, S. K., & Pathak, P. K. (2009). Rich–poor gap in utilization of reproductive and child health services in India, 1992–2005. *Journal of Biosocial Science*, *41*(3), 381-398.

Narooz, R. & Child, J. (2017). Networking responses to different levels of institutional void: A comparison of internationalizing SMEs in Egypt and the UK. *International Business Review*, 26, 683-696.

North, D. C., & North, D. C. (1992). *Transaction costs, institutions, and economic performance* (pp. 13-15). San Francisco, CA: ICS Press.

Obydenkova, A., & Libman, A. (2015). Understanding the survival of post-Communist corruption in contemporary Russia: the influence of historical legacies. *Post-Soviet Affairs*, *31*(4), 304-338.

Olken, B. A. (2009). Corruption perceptions vs. corruption reality. *Journal of Public economics*, *93*(7-8), 950-964.

Padgett, J. F., & Powell, W. W. (2012). The emergence of organizations and markets. Princeton Univ. Press.

Powell, W. W., Packalen, K. & Whittington, K. (2012). Organizational and institutional genesis: The emergence of high-tech clusters in the life sciences”. In: Padgett, J. F., & Powell, W. W. (ed). The emergence of organizations and markets. Princeton Univ. Press.

Puffer, S. M., McCarthy, D. J., & Boisot, M. (2010). Entrepreneurship in Russia and China: The impact of formal institutional voids. *Entrepreneurship theory and practice*, *34*(3), 441-467.

Rao, H. (1998). Caveat emptor: The construction of nonprofit consumer watchdog organizations. *American Journal of Sociology*, *103*(4), 912-961.

Rothstein, B. (2000): “Trust, Social Dilemmas and Collective Memories: On the Rise and Decline of the Swedish Model”, *Journal of Theoretical Politics*, 12: 477-501.

Rodrigues, S. B. (2013). Understanding the environments of emerging markets: The social costs of institutional voids. Rotterdam School of Management, Erasmus University Rotterdam.

Santos, F. M., & Eisenhardt, K. M. (2009). Constructing markets and shaping boundaries: Entrepreneurial power in nascent fields. *Academy of Management Journal*, *52*(4), 643-671.

Scott, W. R. (2001). *Institutions and Organizations*. Second Edition. SAGE.

Seven, U., & Coskun, Y. (2016). Does financial development reduce income inequality and poverty? Evidence from emerging countries. *Emerging Markets Review*, *26*, 34-63.

Shane, S. A. (2003). *A general theory of entrepreneurship: The individual-opportunity nexus*. Edward Elgar Publishing.

Simons, T., Vermeulen, P. A., & Knoben, J. (2016). There’s No Beer without a Smoke: Community Cohesion and Neighboring Communities’ Effects on Organizational Resistance to Antismoking Regulations in the Dutch Hospitality Industry. *Academy of Management Journal*, *59*(2), 545-578

Sine, W. D., & David, R. J. (2003). Environmental jolts, institutional change, and the creation of entrepreneurial opportunity in the US electric power industry. *Research Policy*, *32*(2), 185-207.

Sine, W. D., Haveman, H. A., & Tolbert, P. S. (2005). Risky business? Entrepreneurship in the new independent-power sector. *Administrative Science Quarterly*, 50(2), 200-232.

Suchman, M. C. (1995). Managing legitimacy: Strategic and institutional approaches. *Academy of Management Review*, *20*(3), 571-610.

Transparency International. (2010a), "Corruption Perceptions Index 2010 Long Methodological Brief", available at: http://www.transparency.org/policy_research/surveys_indices/cpi/2010/in_detail#5

Transparency International. (2010b), "Corruption Perceptions Index", available at: http://www.transparency.org/policy_research/surveys_indices/cpi

Weber, B. (2014). Bitcoin and the legitimacy crisis of money. *Cambridge Journal of Economics*, *40*(1), 17-41.

Welter, F., & Smallbone, D. (2006). Exploring the role of trust in entrepreneurial activity. *Entrepreneurship Theory and Practice*, *30*(4), 465-475.

Williamson, O. E. (1979). Transaction-cost economics: the governance of contractual relations. *The journal of Law and Economics*, *22*(2), 233-261.

Winston, C. (1998). US industry adjustment to economic deregulation. *Journal of Economic Perspectives*, *12*(3), 89-110.

Wright, M., Filatotchev, I., Hoskisson, R. E., & Peng, M. W. (2005). Strategy research in emerging economies: Challenging the conventional wisdom. *Journal of management studies*, *42*(1), 1-33.

5.13 Appendix – Table 6: Fixed Effect Regression

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Legal status regulation			-0.346***	-0.340***	-0.140**
			(0.023)	(0.023)	(0.052)
Corruption		-0.048***		-0.037***	-0.025*
		(0.011)		(0.011)	(0.011)
Corruption x Legal status regulation					-0.005***
					(0.001)
GDP per capita	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Internet access (percent)	0.030***	0.035***	0.046***	0.049***	0.060***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Electricity access (percent)	0.197***	0.187***	0.180***	0.172***	0.169***
	(0.010)	(0.011)	(0.010)	(0.010)	(0.011)
Population (ln)	-24.912***	-22.135***	-22.057***	-19.957***	-19.134***
	(2.337)	(2.415)	(2.314)	(2.389)	(2.394)
Number alternative cryptocurrencies	-0.039***	-0.040***	-0.037***	-0.039***	-0.042***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Wallet users (ln)	1.524***	1.515***	1.533***	1.526***	1.527***
	(0.056)	(0.056)	(0.055)	(0.055)	(0.055)
Inflation	-0.042***	-0.041***	-0.042***	-0.041***	-0.042***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Financial stability	-2.570*	-3.902***	-5.413***	-6.396***	-6.009***
	(1.101)	(1.139)	(1.103)	(1.138)	(1.140)
Year dummies	Included	Included	Included	Included	Included
Google bitcoin attention (ln)	0.664***	0.668***	0.653***	0.656***	0.659***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Homicide rate	-0.268***	-0.279***	-0.263***	-0.272***	-0.267***
	(0.021)	(0.021)	(0.020)	(0.021)	(0.021)
Constant	407.078***	362.668***	360.397***	326.823***	311.243***
AIC	25717.691	25699.538	25502.654	25492.332	25475.328
N	8,062	8,062	8,062	8,062	8,062

Legend: † p<.1; * p<.05; ** p<.01; *** p<.001

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