Trading Agent Kills Market Information
Evidence from Online Social Lending

Rainer Böhme[a] and Jens Grossklags[b]

[a] Department of Information Systems, University of Münster, Germany
[b] College of Information Sciences and Technology, Pennsylvania State University, USA

Abstract. The proliferation of Internet technology has created numerous new markets as social coordination mechanisms, including those where human decision makers and computer algorithms interact. Because humans and computers differ in their capabilities to emit and process complex market signals, there is a need to understand the determinants of the provision of market information. We tackle the general research question from the perspective of new electronic credit markets. On online social lending platforms, loan applications typically contain detailed personal information of prospective borrowers next to hard facts, such as credit scores. We investigate whether a change of the market mechanism in the form of the introduction of an automated trading agent shifts the dynamics of information revelation from a high-effort norm to a low-effort information equilibrium. We test our hypothesis with a natural experiment on Smava.de and find strong support for our proposition.

1 Introduction

Credit markets are envisioned to serve as efficient social coordination mechanisms between lenders and borrowers [1]. The idea of online social lending (also known as peer-to-peer lending) is to provide a marketplace for unsecured personal loans. An electronic platform lists borrowers' loan applications so that individual lenders can review this information and decide in which projects they want to invest. Each lender contributes a small fraction of the financed amount. This distributes the credit risk in loan-specific pools of lenders. As compensation for taking risk, lenders receive interest payments, whereas platforms charge fixed (risk-free) fees [2–4].

Traditional institutional lending relies on a number of information sources including hard facts such as requested amount, interest rate, credit rating information and past repayment performance as well as soft facts that consider the wider context of a potential transaction. In online social lending, soft facts find typically consideration in the form of credit profiles that may include an essay description of the project complemented with a picture and other personal information. The careful evaluation of the profile may enable lenders to differentiate between borrowers and to eventually reduce the risk of loan defaults. Additional information typically *allows* for, but not necessarily leads to more efficient contracts [5].

Due to the novelty of online social lending, previous research has focused on the negotiation phase rather than long-term consequences. For example, Böhme and Pötzsch report that references to outside options in the traditional banking sector, even if unverified, are rewarded with better financing conditions. However, statements targeted at arousing pity are penalized [2]. The credit profile helps to reduce the information asymmetry between borrowers and lenders. While requesters of funds might conceal information that would make them appear less desirable [6], they will also pro-actively signal to lenders their credit-worthiness [7]. In summary, in credit markets, information is more important compared to many other financial markets that price more standardized goods [8].

However, the wealth of informally provided information and the growth in popularity of social lending also pose challenges to the efficiency of these marketplaces. In particular, lenders must find ways to overcome the information overload originating from the abundance of loan applications. One option is the creation of reputation schemes to favor well-established and reliable borrowers. A different approach is the consideration of alternative market designs and changes in trading rules [9].

In July 2009, *Smava.de*, a popular German social lending platform, changed its market mechanism by introducing *immediate loans*. Instead of waiting for a posted loan application to be funded, a borrower may consult an automated agent that is suggesting an interest rate high enough so that the loan can be financed instantaneously by lenders who pre-committed offers, resulting in a form of order book. In this paper, we investigate whether the introduction of this automated trading agent shifts the dynamics of information revelation from a high-effort information norm to a low-effort equilibrium. We scrutinize our hypothesis in the form of a natural experiment on *Smava.de* and find strong support for our proposition.

As to the organization of this paper, Section 2 reviews theoretical approaches to the research question, which also include our analysis of the strategic options of market providers, lenders, and borrowers. Section 3 describes our empirical strategy to study the research question with a natural experiment observed on *Smava.de*. The results, presented in Section 4, support our theory both descriptively and, more specifically, by regression analyses of disaggregated data. We offer concluding remarks and present trajectories for future work in Section 5.

2 Incentives of Market Providers and Participants

We are not aware of research on the impact of agents on human-populated online social lending markets, and related work for financial markets is surprisingly sparse. Lin and Kraus survey research on the question whether software agents can successfully negotiate with humans on a variety of commodity markets [10], and Duffy reviews research on markets populated with automated traders in comparison to similar work in experimental economics [11]. In the context of financial markets, software agents are expected to improve market efficiency because they follow predefined rules and do not make mistakes with respect to their algorithms. In addition, software agents can process more data in a given time span and interact faster with the market via APIs than human traders are able to utilize any user interface [12, 13].

We focus the following theoretical discussion on the incentive structure in online social lending considering the different stakeholders: market providers, lenders, and borrowers.

2.1 Rationale of the Market Provider

Online social lending markets are two-sided with significant positive cross-side network effects, i.e., lenders prefer to have a larger group of borrowers to choose from, and vice versa. The intermediary is interested in the overall growth of the platform to reap first-mover advantages to, amongst other factors, erect barriers to entry. To enhance long-term viability, the platform can support matching that will lead to low loan default rates by excluding, for example, untenable risks. Other concerns include the transfer of credit risk to non-banks as well as adherence to financial regulations (e.g., the Dodd–Frank Wall Street Reform and Consumer Protection Act in the United States [14]).

The market provider's profit is derived from closing and late fees and potential future opportunities that may result from the growth of the platform. As a financial intermediary, it is critically important for the market provider to foster an image of professionalism and reliability [15]. One important implication of such an evaluation is the trend towards *uniformity*. In finance, "a preference for uniformity is consistent with a preference for strong uncertainty avoidance leading to a concern for law and order and rigid codes of behaviour, a need for written rules and regulations, [and] a respect for *conformity*" [16]. Such consistency is primarily driven by the evaluation of borrower profiles and can be guided through the default format of these profiles.

The intermediary can further influence the appeal of the platform via market design [9]. A banking report argues that automatic bidding and secondary markets (i.e., the trading of existing loan notes) "inject new professionalism," but also shift attention from humans to artificial agents [17]. As a result, the comprehensiveness of borrower profiles decreases in importance for negotiations that are mediated by automatic agents.

2.2 Rationale of the Market Participants

Lenders Non-bank lenders may understand online social lending as a viable alternative for portfolio diversification, for example, to complement low-risk/low-return certificates of deposit, and stock market portfolios that promise higher expected returns, but come with a significant degree of uncertainty in the short term. The inherent trade-off for online social lenders is the expectation of a relatively high rate of return weighted against the default risk associated with a particular group of borrowers.

However, due to its novelty, we cannot expect a high degree of domain-specific financial literacy within the lender population and, therefore, sufficient expertise to independently avoid borrowers with default risks [18]. The potentially unjustified reliance on soft information in borrowers' profiles might further exacerbate the asymmetric selection problem. In contrast, lenders may derive immaterial benefits from investing in real individuals' aspirations and plans, and learning about them in their self-descriptions.

The crisis in mortgage lending and institutional finance has reopened the discussion about effective protection of non-professional market participants [19]. Further, while online social lending acts as an instrument to escape credit scarcity, borrowers who are not served by traditional banking may also pose additional risks. Taken together, lenders will benefit from marketplace designs that limit overlending as well as contribute to the selection of appropriate credit terms for manageable risks [20].

The existence of an automatic lending agent addresses some of these problems. It limits the search costs that arise from the need to investigate a large amount of soft information and sharpens the focus on verified information. The interaction with the recommendation features of the agent also reduces the likelihood of significant misquoting of interest rates.

Borrowers Borrowers' prime objective is to gain access to financing at reasonable conditions and without other unattractive contractual obligations. Further, the unbureaucratic and innovative nature of online social lending might appeal to individuals with unsuccessful interactions with the traditional banking sector.

Borrowers aim for a favorable evaluation of their loan applications through a number of factors. Borrowers publish a desired amount and purpose, they provide verifiable information about themselves including the credit grade. In addition, a customizable profile allows them to personalize their funding appeal.

The accessibility of personal profiles to every potential lender might, however, be perceived as a privacy risk by borrowers [2]. For example, details about personal finances or unfortunate circumstances could, when used outside of the platform context, cause ridicule by acquaintances or colleagues. The typical interactions with institutional banks and credit bureaus are not immune to privacy concerns [21], however, the open and social nature of online social lending amplifies these worries.

Further, borrowers might also attempt to conceal relevant information [6]. For example, on *Smava.de* over 30 % of all loans are awarded to small business owners or self-employed professionals. It follows that personal credit ratings may not accurately reflect inherent business-related risks [17].

The availability of an artificial agent allows borrowers to choose between automated matching and the human-driven process. The former contributes to an amelioration of privacy concerns, but a weakening of success prospects for individuals with low credit ratings.

2.3 Information Revelation as a Coordination Problem

Borrowers are not only affected by lenders' behavior, and vice versa, but also by the actions of others within their group. For example, past studies have presented evidence for herding behavior with respect to bidding on *Prosper.com*, a US-based online social lending platform [22, 23]. Similarly, the presentation of the personal profile is subject to mimicry. Borrowers copy information from their peers' profiles. Interestingly, they do not seem to copy from successful recent applications more often than from pending or unsuccessful applications [24].

The presence of an automatic agent introduces an unprecedented speed into the process of social lending, as well as an increased focus on verified information. The reliance on the agent may trigger a desire to decrease the provisioning of comprehensive personal profiles to reduce signaling costs. Further, recent behavioral research suggests that the mere exposure to indicators of instant gratification (e.g., fast food symbols) may contribute to a shift of preferences towards economic impatience [25]. It follows that even borrowers who are not directly utilizing the artificial agent may change their behaviors.

The resulting net impact on signaling is far from obvious. In the early years, online social lending platforms have emphasized the social aspect of lending. For example, *Smava.de* advertised its services with the slogan "loans from human to human." This has contributed to a *norm of comprehensive textual signaling* in the form of long personal profiles with the expectation to adhere as a matter of proper conduct [26].

At the same time, our discussion shows that restricted information focused on verifiable facts is unlikely to be inferior from an economic perspective, in particular, considering humans' innate bounded ability of information gathering and processing [27, 28].

Considering the information revelation of borrowers as a coordination problem is helpful to understand the dynamics of their behavior on *Smava.de*. We argue that different jointly chosen degrees of soft information revelation can be equilibria, and it depends on exogenous coordinating factors which outcome is reached [29]. For example, the user interface design for personal profiles as well as *Smava.de*'s framing as a human-to-human lending platform jointly served as a focal point for a high degree of information revelation. In contrast, the introduction of the artificial agent is a strong driver for brevity.

More specifically, we can describe the coordination between borrowers where lenders react as follows. When lenders make their funding decisions, they cannot know the true value of soft information (compared to hard verifiable information). Hence, they estimate it by observing the usage of soft information in the marketplace (i.e., the average of all soft information revealed). If the majority of borrowers reveal no information then lenders would reckon that such soft information is of no value. In contrast, a market in which borrowers heavily utilize soft information would suggest to lenders that such information has value.

From this basic premise at least two potential outcomes may result. At the one extreme, if none of the borrowers reveals any soft information, then it follows that none of the borrowers could improve his position by revealing soft information as the cost of revelation is positive and the value of revelation is zero. In contrast, if all borrowers reveal soft information, then any borrower would harm his position by not including soft information. While on the one hand, the borrower could reduce his cost by omitting soft information, the loss of apparent creditworthiness (from the perspective of lenders) outweighs this benefit. In that sense, soft information is productive.

The introduction of the trading agent has the potential to change the focal point since those borrowers who use loan matching by the trading agent know that adding soft information does not influence the lending decision. Lenders, however, have no direct means to tell loans matched with a trading agent and conventional loans apart. Hence, their estimated value of soft information is impacted by the mixture of the two regimes. As the share of automatically matched loans exceeds a certain threshold, the market will tip towards low information revelation.

The distribution of individually heterogeneous costs for information revelation and lenders' belief structure influence the strength of the described processes and the threshold of the tipping point which motivates an empirical analysis. We hypothesize that the amount of soft information provided on *Smava.de* decreases after the introduction of the trading agent independent of whether the trading agents has been used by an individual borrower.

3 Empirical Strategy

3.1 Institutional Background

Smava.de, established in February 2007, is the largest online social lending platform in Germany handling a total of €77 million allocated to about 9000 loans (as of July 2013). Unlike *Prosper.com*, the dominant platform in the US, *Smava.de* does not use an auction mechanism. Instead, borrowers post loan applications including amount, interest rate, and maturity along with verified demographic information (age, occupation, state of residence) and a credit grade between A (best, nominal default risk $< 1.3\,\%$) and H (worst, default risk $17\,\%$). These applications serve as take-it-or-leave-it offers for lenders, who decide if and how much (in units of €250) they want to contribute to financing each pending loan. Loan applications are settled when they are fully funded or after two weeks. Borrowers have the option to revise the interest rate upwards if the loan does not receive funding as quickly as desired. They may also complement their loan application by unverified information, such as textual descriptions, motivation statements, or custom pictures. We use this voluntary provision of information as indicator for revelation behavior.

Figure 1 depicts a typical profile on the platform. In this example, a potential male borrower applies for an amount equivalent to $7000 to finance education expenses to become a certified optician.

Smava.de introduced and gradually extended automatic trading agents to assist their lenders. A more substantial change was the introduction of an automatic loan placement agent in July 2009. This agent assists borrowers in finding the currently relevant interest rate such that a loan application would immediately be approved by the lenders' trading agents. In other words, the new

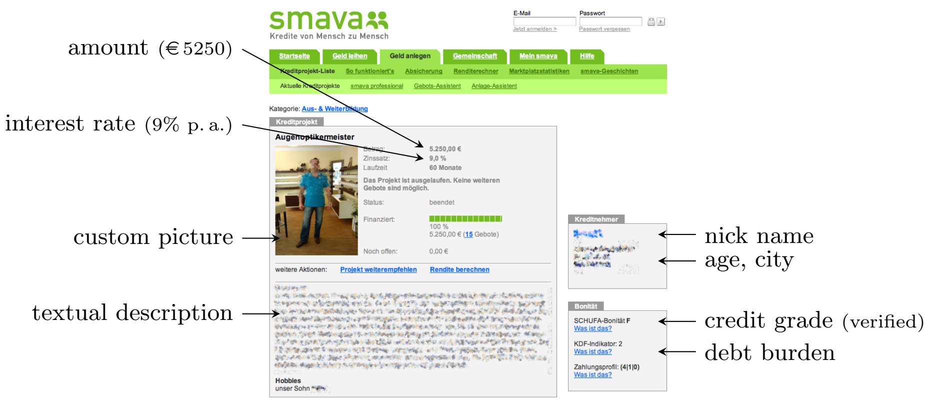

Fig. 1. Example credit profile of a male applicant to finance certifications to become a professional optician. (Contents obfuscated by the authors for borrower privacy.)

agent reinterprets the parameterization of the lenders' trading agents—all controlled by the platform—as an order book, and replaces the take-it-or-leave-it mechanism by a matching mechanism.[1]

Since July 15th, 2009 both mechanisms coexist. This forms a unique natural experiment to study not only the influence of trading agents on information revelation in the part of the market served by the agents, but also on the rest of the loans which continue to use the old mechanism.

3.2 Data

Our study uses public information only. We downloaded all $N = 931$ loan applications listed on *Smava.de* between April and October 2009. This sample has been split into contrast groups consisting of 380 loan applications before and 551 applications after the intervention. We remove the month of July to exclude all loan applications that overlap the intervention date (see Figure 2).

Our *independent* variable is the presence of the trading agent for borrowers. We measure our *dependent* variable, information revelation, by two proxies. First, we follow Herzenstein *et al.* [4] and measure the length of all unverified descriptions of a loan application and the attached borrower profile in characters. Within each contrast group, this variable can be reasonably approximated with a Gaussian distribution after taking logs (see Figure 3). The second indicator of information revelation is inspired by Pope and Syndor [30]. We take the binary fact whether or not borrowers illustrate their loan applications by uploading custom pictures which replace the default icon defined by *Smava.de*.

We do not try to measure the semantics of the description or the picture, i. e., whether they contain any relevant information or valence. As even in the "before" condition, only one quarter of loan applications is illustrated with a

[1] The basic process is similar to Priceline.com counteroffers.

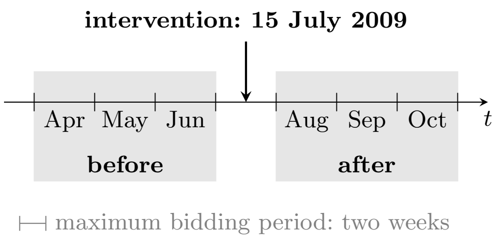

Fig. 2. Design of the natural experiment analysis

custom picture, it is fair to assume that borrowers will only upload carefully selected pictures which they believe help their cases. Likewise, writing longer descriptions is associated with opportunity costs and privacy loss.

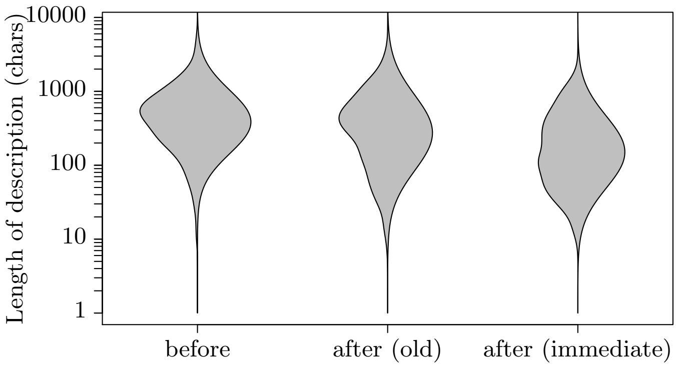

Fig. 3. Length of description: Violin plots of smoothed empirical distribution (left) and log normal fit (right) for contrast groups compared in this study (Gaussian kernel, bandwidth 0.5, $N = 931$)

Moreover, we collected a number of *control* variables which might interact with the hypothesized relationship. Most importantly, we try to identify whether a loan has been granted using the old or new mechanism in the "after" condition. This information is not directly visible on the platform and has been inferred from the succession of bid times, which are available at a resolution of one minute. Agent-matched ("immediate") loans are characterized by complete funding whereby no two bids differ by more than one minute. All other loans are classified as take-it-or-leave-it ("old"). In addition, we collected the amount, interest rate, credit grade, and the assignment to one of 19 credit categories[2] for every loan application in the sample.

[2] The categories on *Smava.de* are: debt restructuring; liquidity; home, gardening & do-it-yourself; cars & motorbikes; events; education & training; family & education; antiques & art; collection & rarity; electronics; health & lifestyle; sports & leisure;

Table 1. Activities on the *Smava.de* marketplace before (Apr–Jun '09) and after (Aug–Oct '09) the introduction of the automatic loan placement agent

	Before	After	
		all	old[1)]
Volume			
Number of loans	380	551	378
Financed amount (€ millions)	2.9	4.7	3.5
Credit conditions			
Avg. interest rate (% p. a.)	10.2	8.7	8.5
Commercial bank rate[2)]	5.1	5.1	—
Credit quality			
Investment grade (A–C in %)	43.7	46.6	43.4
Signaling			
Median length of description	456	271	332
Provision of custom picture (%)	25.5	11.3	15.3

[1)] loans using the old take-it-or-leave-it mechanism
[2)] central bank statistics of market interest rates

4 Results

4.1 Descriptive Analysis

Table 1 shows aggregated statistics broken down by the contrast groups before and after the intervention. The "after" condition is further refined by a separate column for loans using the old take-it-or-leave-it mechanism. One can observe three major effects to be discussed in the following.

The number of loans grew by 45 %. At first sight, it looks like immediate loans tap into a new segment, as the number of loans using the old mechanism is almost constant. The average loan amount grew by 12 % with a tendency for larger loans to use the old mechanism while smaller loans are matched through the trading agents. The observed development is in line with our analysis of the market provider's strategy (Sect. 2.1). But the evidence is relatively weak because the general growth path of the platform impedes a direct causal attribution to the intervention.

The average interest rate dropped by 1.5 %-pts with immediate loans being marginally more expensive than take-it-or-leave-it loans. The latter discrepancy can be explained by time preferences. This development is remarkable because we can rule out third factors such as general trends in consumer credit interest rates. The official statistics of comparable loans to consumers of traditional banks report stable and significantly lower interest rates. The level shift is due to higher

travel; pets & animals; volunteering; commercial; business investment; business extension; miscellaneous.

quality requirements in the banking sector compared to *Smava.de*. The drop in interest rates after the intervention cannot be explained by a significant change in average credit quality, either. The fact that immediate loans exhibit slightly higher credit quality may in fact be due to inverse causality: high-quality (i. e., low risk) borrowers have an outside option in the banking sector, which becomes comparably less attractive if the interest rates on *Smava.de* decline.

Note that we must not interpret this result as support for the hypothesis that trading agents improve market efficiency. Unless we observe actual default rates, it is too early to tell if the borrower-friendly low risk premium is in fact closer to the equilibrium price of risk on *Smava.de* [31].

Both indicators of information revelation, length of description and provision of custom picture, show a substantial decline after the intervention. Interestingly, this is not limited to the immediate loans (where the effect is most pronounced because the agents do not evaluate unverified information). So the presence and visibility of agent-matched deals appears to spill over and change the information revelation conventions on the *entire* marketplace.

Superficially, these numbers already tell a story. But the evidence for this interpretation from Table 1 alone is weak. Market expansion, borrower-friendly conditions, and other effects might interact with each other and lead to spurious results in the aggregated numbers. For example, an alternative explanation could be that lower interest rates have attracted better risks with more self-explanatory credit projects. To gain more robust insights, we conduct a disaggregated analysis on individual loans for the phenomenon of disappearing information.

4.2 Regression Analysis

To isolate the effect of the introduction of a trading agent on information revelation from other shifts in the market conditions, a series of multivariate regression models has been estimated. First, we explain the length of description (ℓ) with the following equation,

$$\log_2 \ell_i = \beta_1 A_i + \beta_2 R_i + \beta_3 T_i + \beta_4 I_i + \boldsymbol{c}\boldsymbol{C}_{(i,\cdot)} + \boldsymbol{g}\boldsymbol{G}_{(i,\cdot)} + \varepsilon_i, \tag{1}$$

where A_i is the log amount, and R_i is the interest rate in percent p. a. of loan i. T_i is a dummy variable taking value 1 if the loan has been listed *after* the introduction of the trading agent, 0 otherwise. I_i takes value 1 if the loan is an "immediate loan", i. e., it has been financed by using the trading agent. Matrices $\boldsymbol{C}$ and $\boldsymbol{G}$ contain a series of dummy variables as fixed effects for 19 credit categories and 8 credit grades, respectively. Equation (1) is estimated using ordinary least squares, i. e.,

$$(\hat{\beta}_1, \hat{\beta}_2, \hat{\beta}_3, \hat{\beta}_4, \hat{\boldsymbol{c}}, \hat{\boldsymbol{g}}) = \arg \min_{(\beta_1,\ldots,\boldsymbol{g})} \sum_{i=1}^{N} \varepsilon_i^2. \tag{2}$$

Table 2 reports the estimated coefficients for a stepwise inclusion of the T_i and I_i terms along with statistical significance tests of the null hypothesis $\beta = 0$.

Table 2. Results of regression analyses: Effect of presence and use of trading agent on information revelation while controlling for credit volume, conditions, and quality

	Length of description ($\log_2 \ell$)		
Terms	M1	M2	M3
Amount [log]	0.24^{***}	0.35^{***}	0.30^{***}
Interest rate [%-pts]	-0.07^{*}	-0.21^{***}	-0.16^{***}
Trading agent present		-1.14^{***}	-0.91^{***}
Trading agent used			-0.49^{**}
Category fixed effects	yes	yes	yes
Credit grade fixed eff.	yes	yes	yes
Adjusted R^2 [%]	3.7	13.2	14.0

Sig. levels: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$; $N = 931$

M1 is the default model over both periods together. It identifies a highly significant positive correlation between the length of description and the amount (both in logs): borrowers who ask for more money are willing to explain their project better. We also find a significant negative correlation between interest rate and length of description suggesting that borrowers who are less verbose are penalized ceteris paribus with (slightly) worse credit conditions. All predictors in M1 explain less than 4 % of the variance of the dependent variable. This is because the hidden heterogeneity—the regime change—is not reflected in this specification.

Models M2 and M3 include a term for the presence of the trading agent, which adds another 10 %-pts of explained variance. The coefficient is negative—indicating disappearing information—and highly significant. This supports our above hypothesis with strong evidence on the micro-level and after controlling for third variables. The effect of the intervention can be further decomposed on the individual loan level to isolate contributions from the mere presence of a trading agent and the fact that the trading agent was actually used to settle a particular loan. This is realized in M3. Interestingly, the platform-wide effect is responsible for the lion's share in the decline of signaling whereas the actual use of the trading agent is of subordinate importance. We interpret this as support for a switch in the equilibrium situation stimulated by the option to use the new mechanism.

Regression diagnosis via inspection of the residual distribution and fixed effects coefficients revealed nothing surprising or worrying. For example, categories with positive significant fixed effects include events, volunteering, and business extensions; arguably the least self-explanatory ventures. Post-hoc ANOVA checks between M1 and M2, as well as M2 and M3, respectively, indicate highly significant differences in explained variance.

A remaining doubt is that detailed information might have disappeared due to a gradual shift in the conventions on *Smava.de*, which would be confounded with our natural experiment. To test this, we re-estimated M3 including a lin-

Table 3. Effect of trading agent on provision of custom picture

	Log odds ratio of custom picture		
Terms	Model 4	Model 5	Model 6
Amount [log]	0.1	0.3 *	0.2
Interest rate [%-pts]	−0.1	−0.3 ***	−0.2 *
Trading agent present		−1.5 ***	−1.1 ***
Trading agent used			−1.7 **
Category fixed effects	yes	yes	yes
Credit grade fixed eff.	yes	yes	yes
Pseudo-R^2 [%]	8.8	16.8	18.8

Sig. levels: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$; $N = 931$

ear time trend as additional term. The coefficient (-0.001, $p = 0.44$) indicated no prevalence of a persistent time trend between April and October 2009. This strengthens the evidence that the observed differences before and after the introduction of the trading agent were indeed caused by this intervention.

A second indicator of information revelation is the provision of a custom picture. This is a binary indicator, and we use logistic regression analysis to regress the predictors of Equation (1) on the log odds ratio for the provision of a custom picture. The resulting coefficients, as reported in Table 3, have to be transformed to the probability domain to interpret their absolute magnitudes. Nevertheless, it is straightforward to interpret their sign and relative size.

Provision of a custom picture is a cruder indicator. Hence, the terms for amount and interest rate are barely significant, yet estimated with plausible signs. Again, after controlling for third variables, the intervention has a strongly significant negative effect on the willingness to provide custom pictures. Note that model M6 attributes a larger contribution to the actual use of the trading agent than to its mere presence.

4.3 Limitations

Natural experiments with a single intervention date suffer from the difficulty to exclude unobserved third variables as causes. Therefore, they do not permit causal inference in a strict sense. Although, we controlled for observable factors and linear time trends, there may be non-linear dynamics of growth or overlapping interventions we are not aware of.

We intentionally avoided conjectures about efficiency or welfare aspects of information revelation regimes. Reliable empirical statements on market efficiency and long-term costs or benefits of signaling in this marketplace depend on the availability of actual default rates. These cannot be observed before the 3–5 year maturity of the outstanding loans has been reached.

5 Conclusions

To the best of our knowledge, this work is the first attempt to study the effect of automatic trading on information revelation behavior in marketplaces where humans and computers interact. We have theorized how voluntary disclosure of unverified information forms a coordination problem with at least two equilibria for high, and respectively low information regimes. A natural experiment in the context of online social lending, an information-rich market, enables us to test our hypothesis empirically and study the effects of the introduction of an optional trading agent on information revelation. The latter was measured by two quantitative indicators. While controlling for third variables, both were found to be negatively affected by the introduction of the trading agent.

Generally speaking, our results illustrate how changes in the market mechanism, even if limited to parts of the market, may reset focal points and cause spillovers to rebalance the equilibria in the initially unaffected segments of the market. If this logic is transferred to other markets, or more generally to coordination games (e.g., real-name policies in virtual communities), then utmost care should be taken when introducing automated agents. Even if the automation is optional and affects only part of the market or community, an avalanche effect might follow and its precise consequences are difficult to predict in advance.

We believe that this opens an interesting and relevant direction with many research questions. Obvious next steps include the differentiation of signals on a semantic level [2], or the interpretation of the temporary shut-down of the US social lending platform *Prosper.com* as a natural experiment [32].

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