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LENDING ROBOTS AND HUMAN CROWDS: INTEREST RATE DETERMINATION ON A REVERSE AUCTION PLATFORM

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Research paper

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Abstract

We analyze the determinants of the level of interest rates related to business loans traded on digital crowdlending platforms. We consider one of the leading platforms in France and collected original data on all the projects financed via this platform. On that platform, interest rates are set by the crowd of investors through a reverse auction process. We show that the loan characteristics and the scoring provided by the platform significantly influences the interest rate. However, though financial ratios are used traditionally to estimate credit risk, those ratios do not exhibit significant influence. Besides, we analyze the impact of the recent implementation of an automated auction mechanism. This implementation seems to have a large impact on both auction duration and on the determinants of interest rate. This suggests that use of a robot impacts on price and saving allocation on this platform-based credit market.

Keywords: Crowdlending, Reverse Auction, Credit Risk, Lending robots

1 Introduction

Since the mid-2000s, the financial sector has experienced disruption from a major crisis which has questioned the traditional channels for the distribution of capital allocations. New technology driven-innovation was seen as a natural alternative to and a new way of linking economic agents for financing purposes (Kremp and Piot 2015). The European compared to the United States peer-to-peer (P2P) lending market exhibits various characteristics that provide an original context. A key difference is the fact that historically, European financial systems (excluding the UK but including France and Germany) were strongly bank-based while the United States system originally was essentially market-based (Levine 1999, Mollick 1999). That institutional history helps to explain the recent and disparate growth of the crowdlending business in France. The credit crunch that followed the subprime crisis in 2008 and new banking regulation (Capital Requirement Directive in Europe) led to a sudden lack of liquidity for small and medium sized enterprises (SMEs) in France. Moreover and in contrast to market oriented systems areas, French securities markets were not sufficiently developed nor sufficiently accessible to SMEs which opened the way to P2P alternatives. However, growth in crowdlending especially in

France, up to 2014 was constrained by relatively unfavorable regulatory frameworks[1], and a strong cultural tendency for small investors and SME managers to be captive to banking facilities (BNP Paribas 2016).

Consequently, on the one hand, most individual lenders lack financial expertise and suffer from asymmetric information, and on the other hand, platforms struggle to attract SMEs. Online borrowers/businesses exhibit heterogeneous and sometimes unconventional profiles uneasy to evaluate profiles (Pouey International 2016). That involves young age, immaterial assets, and innovations. The competitive landscape of crowdlending platforms in France is characterized by a variety of business models and has yet to stabilize around a particular *modus operandi*. For instance, platforms display different maximum loan amounts and loan durations. They also use different ways to determine the levels of interest rates imposed on each project. In some cases, the interest rate is established by an expert committee of the platform (Credit.fr, Lendix, Lendopolis, Pretup). In other cases, it is the responsibility of the crowd of lenders, and relies mostly on a reverse auction mechanism (Finsquare, Unilend). In that case, the platform can be more or less of a digital vector of the interest rate determination: auctions bids can be free, covered by minimum and maximum rates, or oriented to use of lending robots (Unilend). The holding of SME loans by a population of unqualified investors raises certain questions. Traditionally, financial ratios and credit scoring are key variables in credit risk assessment, and the interest rate is an objective output of a financial analysis process. In a reverse auction process of interest rate determination by human crowds, interpretation of financial statements by unqualified lenders could lead to wrong estimation of the counterparty risks (Mild e*t al.* 2015). In order to assist lenders in their investment strategies, crowdlending platforms provide a full set of financial and non-financial information on each project. Unilend is the first platform to implement a lending robot (Autolend) in the French crowdlending market with the stated purpose of helping lenders to diversify their portfolios.

The objective of our paper is to analyze the process of interest rate determination by a human crowd which financial literacy is uncertain and that has the opportunity to activate a lending robot to facilitate bid strategy. To study how these new crowdlending feature affect the lending process, we focus on Unilend, one of the largest and oldest crowdlending platforms in France. Following a brief literature review in section 2, section 3 develops an econometric analysis of average interest rates on Unilend, before and after the introduction of its lending robot. Our results shows that the two main artefacts available to human lenders on the platform - the score and the lending robot - are the main drivers of interest rate levels. Conversely, traditional financial ratios have little influence in the risk valuation process.

2 Related literature

The digitization of financial services is being increasingly scrutinized by management and information systems (MIS) researchers[2], along with the large number of papers dedicated to crowdlending. Gleasure and Feller (2016) provide an exhaustive analysis of the academic literature on crowdfunding. They find that crowdlending is the most popular crowdfunding research topic, and especially among studies using a quantitative econometric approach. In our paper, we propose to link the lending robot phenomenon to interest rate determination which links it to both a MIS and a financial perspective.

According to Lebraty (2006), crowdlending platforms are particularly suited to the inclusion of lending robots. US crowdlending platforms pioneered the development of [3] lending robots, while, to date in France, only two platforms offer their customers use of a lending robot. These two platforms are Unilend with Autolend since 2016, and Wesharebonds with WeBot in 2017. Since determination of interest rates

[1] In France the so-called “banking monopoly” prohibits anyone other than a bank to purchase any form of loans. A new French regulatory framework for crowdlending came into force in 2014, and allows digital platforms to arrange up to €1 million of financing for businesses.

[2] This is exemplified by the latest call for papers from the *Journal of Management Information Systems*: “Financial IS, Underlying Technologies and the FinTech Revolution”, and the ECIS2017 track “FinTech and the digitization of financial services”.

[3] Cf. Forbes (12 Mars 2017) : « The Best P2P Lending Automation Tools for Investors”

is entrusted to the crowd, the result of the process relies overwhelmingly on use of automation. (Franks et al. 2016, Lee and Lee 2012). Böhme and Grossklags (2013) were the first to study the effects of introducing an optional lending robot into the revelation of information. They showed that the amount of "soft" information provided on a German P2P platform decreased after introduction of a trading robot. The main reason for this is that the automation (the robot) has the potential to change the focal point since those borrowers who use loan matching by lending robot know that adding soft information will not influence the lending decision. The novelty of our paper is that the platform studied does not use a take-it-or-leave-it model but rather an auction mechanism in which borrowers post interest rates. Moreover, our work focuses more on the link between lending robots and lenders' expertise, and less on the learning process from the dissemination of borrowers' information after introduction of the robot.

In relation to the financial aspects of the lending process, financial and extra-financial variables can influence the outputs of the reverse auction mechanism (Herzenstein and Dholakia 2011). According to Realdon (2013), the term structures of credit spreads on corporate bonds and credit default swaps traditionally are linked to pro-forma financial statements. However, the rates observed on crowdlending platforms can deviate from fundamental credit risk analysis because of the crowd's lack of expertise (Franks et *al*. 2016, Mild et *al*. 2015). Zhang and Chen (2017) show the presence of herding behavior, and highlight the responsibility of the platform to inform, educate, and pre-select SMEs. Mollick and Nanda (2016) find significant agreement between the funding decisions of the crowd and those of the experts in the context of cultural (i.e. theater) projects. Zhang and Liu (2015) explore the herding mechanism and the extent to which each lender is able to process the listing information. They find evidence of sophisticated, rational herding. Dietrich and Wernli (2016) analyze the determinants of consumer loan interest rates in the Swiss crowdlending market. They find that loan-specific variables produce both statistically and economically significant results. But the study is based on a specific platform dedicated to consumption credit for individual households. The absence of any accounting information does not allow then to illustrate the possible lack of expertise and financial literacy previously mentioned.

In addition to this lack of expertise, Mitchell et al. (2017) also stress the time constraint as another factor which can influence the information processed by the crowd. Indeed, credit risk management can be time consuming for non-financial experts or non-financial workers. In such a case, the time allocated for investment management is detrimental to the acquisition of other professional skills and thus to the personal carrier's evolution. In order to mitigate this problem, the platforms can also integrate decision support systems – DSS - (Lebraty, 2006, Gleasure and Feller 2016). This innovation is relatively widespread in the United States[4] though it is more recent in France: Autolend was launched by Unilend on its platform in 2016. Wesharebonds also introduced a webot in 2017. Thus, the formation of interest rate will depend on the combination of the DSS and of the online transaction processing – OLTP – architecture (Franks and al., 2016). Böhme and Grossklags (2013) have analyzed the impact of the introduction of lending robot on the use of information by the lenders within the framework of a German platform P2P. According to their study, introduction of the robot led to strengthen the role played by hard and non-expert information under the form of simplified signal such as rating as main drivers of interest rates levels.

To the best of our knowledge, the present analysis, dedicated to interest rates determination by crowdlenders, is the first attempt to directly link MIS and financial academic research. First, we analyze the extent to which the crowd is able to use the fundamental standards of risk valuation. Second, we explore the effect of introducing a lending robot. Our goal is not to demonstrate or explain herding behavior but rather to complement those bottom-up approaches by a top-down approach based on the explanatory variables for interest rates. We aim to determine the degree of crowd's ability to use hard and expert information, and the influence of an investing decision-support system.

[4] Cf. Forbes (12 March 2017) : « The Best P2P Lending Automation Tools for Investors". [https://www.forbes.com/sites/oliviergarret/2017/03/12/the-2-best-p2p-lending-automation-tools-for-investors-detailed-analysis/#4cdb14061fde].

3 Data and methodology

Our methodology has similarities with the method proposed in Dietrich and Wernli (2016) and involves the collection of hard information on borrowing projects in the French Peer-to Business (P2B) lending market to analyze the main drivers of average interest rate determinations. We first present the Unilend platform and categorize the various types of hard information likely to be used by lenders (3.1.). We then elaborate on the data collection process, describe the data sample and present the estimation procedure (3.2.).

3.1 Presentation of the Unilend platform

Unilend is a French crowdlending platform specialized in loans to SMEs. Since its creation in 2013, the platform has raised funds for more than 400 projects to a total of over 30 million euros[5]. The borrowers are based in the French territory and show a high level of sectoral variety. With the exception of real estate acquisitions and loan repurchases, all of the projects can be accepted including cash refinancing and immaterial assets projects. Loans are repayable at between 3 and 60 months, and cover amounts from €10 000 to €500 000. SMEs have to prove they have been operating for at least of 3 years, and franchises are eligible. For each project, Unilend provides a credit risk analysis in the form of a rating from 1 to 5 stars. This rating is extracted with the following weighting: 40% from a proprietary algorithm that automatically collects qualitative and quantitative data, 20% based on borrowers' financial data, 20% based on industry-level data, and 20% based on judgments about the quality of the borrower's management. Only projects that receive a minimum 3-star rating are allowed to enter the lending process. Once the campaign launched, potential lenders determine (but do not disclose) their investment bid (€20 at least) and the lowest rate at which they are willing to fund the loan. The auction starts at the maximal interest rate (which is given by the platform considering both Unilend rating and loan duration) and continues as lenders bid lower and lower until either the end of the auction period decided by the borrower or once the lowest interest rate (also set by the plaform) has been reached. Lenders can update their bid at any moment during the campaign. At the end of the reverse auction period, the borrower selects the most competitive bids until the amount requested is reached. If the amount required is not achieved, the campaign is cancelled. Since April 2016, Unilend has offered to lenders the option to activate Autolend, a lending robot that can automate auction bids. In the simple version of Autolend, lenders can set the per project amount they wish to lend, and the desired minimum rate. In its advanced version, the lender with the help of a double entry table, can set different interest rates depending on the loan duration and the Unilend rating.

The information available for each project includes hard information such as loan characteristics (auction length, loan duration, requested amount, rating) and key figures from the borrower's financial statement (available in a downloadable excel version for the calculation of ratios). Potential lenders also have access to soft information such as the nature of the project, and the history and objectives of the business. Additional soft and hard information can obtained by lenders from other sources outside of the platform such as social media, SME's website, online discussion forums, financial and sectoral SME databases (generally on a pay-per-use basis). Thus, the lending crowd has to handle different sets of information which can be categorized into various dimensions: soft (qualitative and textual) and hard (quantitative and numerical), direct (within the platform) or distant (outside of the platform), unprocessed or processed (with calculation), objective (fact) or subjective (opinion), expert (i.e. whose interpretation requires specific skills such as financial statements), and non-expert (Unilend rating).

It is traditional in corporate banking for credit risk valuations to be considered as influenced mainly by hard information (financial statements and financial performance compared to similar businesses in the same sector). Soft information is used to refine the valuation (Artis & Cornée 2016). Standard financial indicators such as debt, liquidity, and margin ratios are used to quantify the borrower's default probability (Driga et *al.*2010). Thus, the main drivers of credit risk valuation which determines the interest rate are based mainly on hard, processed, and expert information. An important issue related to interest

[5] Source : Unilend, April 2018.

rate determinations by a human crowd is identifying whether the drivers of credit risk valuations are linked to the same fundamental analysis as banking expertise. We propose to test the sensitivity of interest rates to traditional credit risk analysis proxies. Based on the results, we will explore usage of bid automation in the lending process since 2016. We are interested in whether it is significant and how it changes the dynamics of interest rates setting. In a second step, we compare the two samples before and after the introduction of Autolend.

3.2 Data description

We collected data on the Unilend platform and observed all the projects launched on that platform (from December 2013 to June 2017). For each project, we observed i) lender-specific characteristics (source: Unilend platform); ii) borrower-specific financial information (source: Diane database), and iii) sector-specific financial information (source: Diane database). To perform the econometric analysis, we excluded projects from those firms whose financial characteristics were not observable in the Diane database. We excluded firms whose crowdlending campaigns were successful but which eventually chose not to issue the loan, and excluded also firms that did not meet their financial target and so were not granted a loan. We are left with 204 observations. Collected data are defined in Table 1.

Variable name	Variable description
avintrate	Average (post campaign) interest rate, in percentage
principal	Financial Target (i.e. loan size), in thousand €
duration	Loan duration, in months
lendersnb	Number of selected lenders
rtUnilend	Unilend rating, from 3 to 5
tu_m_refy	Borrower's annual turnover in the reference year, in million €
auction_time	Actual duration of the auction process, in days
repaycap	Borrower's repayment capacity
fibal	Borrower's financial balance ratio
opmargin	Operating margin
avgap_ocf	Gap between the borrower's operational cash flow and the sector's average operational cash flow
avgap_opmargin	Gap between the borrower's operating margin and the sector average operating margin

Table 1. Variable description

Table 2 presents the descriptive statistics of the sample before and after introduction of Autolend. The descriptive statistics suggest that Autolend induced changes in the behavior of lenders and borrowers. On average, post-Autolend auction duration reduced by two-third; thus, after introduction of Autolend borrowers can expect lenders to react more quickly. In Autolend-assisted crowdlending campaigns, one in two projects achieves its target in less than one day(<1 day). Therefore, assuming a sufficiently high number of lenders, borrowers have less need to set a long auction duration in the belief that greater lender competition will translate into lower interest rates.

Second, all other things being equal, the number of lenders per project almost doubled after the introduction of Autolend (427.25 vs. 844.56). Lenders who prefer manual input mode need to log on to the platform in order to adjust their bids in the final minutes before the auction closes (late bidding strategy). Automatic lending removes this constraint and makes the auction process more attractive.

Autolend seems also to have a negative impact interest rates (8.29% vs. 6.68%). We performed a mean difference test. The t-statistics assuming either equal or unknown variance reveal that the mean difference is statistically significant (resp. t=9.83 or 9.75, 1% precision level). The competition effect associated with a larger number of lenders is a plausible explanation for this difference. However, this explanation does not account for the variation in other factors. The econometric analysis allows us to control for the impact of these factors.

	Prior to Autolend introduction					After Autolend introduction				
Variable name	**N**	**Mean**	**Std.**	**Min**	**Max**	**N**	**Mean**	**Std.**	**Min**	**Max**
Avintrate	244	**8.29**	1.40	4	9.9	113	**6.68**	1.38	4	9.3
Principal	244	78.78	56.91	10	400	113	74.66	68.86	10	300
Duration	244	43.54	12.74	6	60	113	36.29	16.94	6	60
Lendersnb	235	**427.25**	270.71	98	1867	104	**844.58**	595.07	141	2955
rtUnilend	243	3.38	0.48	3	4.5	113	3.32	0.36	3	4.5
tu_m_refy	244	1.96	5.96	0	83.53	113	1.21	1.69	0	13.22
auction_time	233	**12.08**	7.42	2	45	108	**3.94**	5.52	1	28
Repaycap	167	2.93	5.14	-14.6	46.23	54	5.25	9.88	0	66.45
Fibal	167	3.91	17.70	0.50	221.67	54	2.841	2.391	0.86	13.27
Opmargin	168	11.74	11.21	-9.11	72.22	54	7.43	12.74	-72.34	28.858
avgap_ocf	162	1.29	6.74	-65.9	38	53	4.19	8.77	-9.37	27.85
avgap_opmargin	163	1.19	4.23	-29.6	27.1	53	2	3.07	-3.85	8.98

Table 2. Descriptive statistics[6]

3.3 Econometric analysis

We performed ordinary least square (OLS) analysis on the following relationship:

$$Average\ interest\ rate = avintrate = constant + \alpha_1 * principal + \alpha_2 * duration + \alpha'_2 * duration^2 + \alpha_3 * lendersnb + \alpha_4 * rtUnilend + \alpha_5 * tu\_m\_refy + \alpha_6 * auction\_time + \alpha'_6 * auction\_time^2 + \alpha_7 * repaycap + \alpha_8 * fibal + \alpha_9 * opmargin + \alpha_{10} * avgap\_ocf + \alpha_{11} * avgap\_opmargin + \varepsilon$$

where dependent and independent variables are defined in Table 1.

To assess the impact of Autolend introduction, we performed OLS on two different samples (prior to and after Autoled introduction). Results are presented in section 4. We introduced *duration²* to enable identification of non linear effects as yield curves typically exhibit a concave shape[7]. We also introduced a squared term for *auction_time* since the effect of auction duration on interest rate may not be monotonic. On the one hand, a longer duration may reinforce competition between lenders and lower the average final interest rate. On the other hand, some lenders may be deterred to bid because of a long duration since lender selection by the platform and loan repayments should begin only after the auction period. All things else equal, this may have a negative impact on the number of lenders interested in the project. Introducing a non linear term enables identification of those effects. We also conducted several robustness checks based on alternative sets of independent variables. These confirm the results. In Appendix, we also provide estimates on the whole sample (with *autolend* defined as a dummy variable, 1 if *autolend* is available to lenders, 0 else). In Appendix, we also provide estimates on the whole sample using variable $automate$ as a co-factor. These estimate enable a general assessment of the effect of Autolend introduction - as measured by the *autolend* variable - on the average level of interest rates. Unlike the subsample analysis, this assumes that the role played by other exogenous variables is constant whatever the period.

[6] The number of observations changes due to missing variables for some observations.

[7] See anecdotal evidence on US on https://www.treasury.gov/resource-center/data-chart-center/interest-rates/Pages/TextView.aspx?data=yield, last consulted April 2018, 9th.

4 Results

4.1 Prior to Autolend introduction

Table 3 presents the results of the econometric analysis with the endogenous variable the interest rate level (in % points). Column (a) considers the situation before the introduction of Autolend. We observe first that the coefficients of all the project-specific variables exhibit the expected signs. A marginal increase in the loan duration (ranging between 6 and 60 months) has a positive impact on the interest rate, with the coefficient of the variable *duration x duration* showing that this effect is not linear with respect to *duration*. This is in accordance with the yield curve commonly observed in financial markets. The loan size also affects the interest rate positively. Both effects can be explained by an increase in the risk associated to longer loan duration or larger loan size.

	Prior to Autolend introduction (a)		*After Autolend introduction (b)*	
	Average interest rates		Average interest rates	
principal	0.0121***	(0.00226)	0.0155	(0.0103)
duration	0.193***	(0.0354)	0.0590	(0.0435)
duration x duration	-0.00182***	(0.000418)	-0.000210	(0.000610)
lendersnb	-0.00128**	(0.000468)	0.000461	(0.000729)
rtUnilend	-0.469**	(0.162)	-1.159*	(0.499)
tu_m_refy	-0.0267	(0.0265)	-0.0823	(0.0757)
auction_time	0.138***	(0.0372)	-0.0542	(0.108)
auction_time x auction_time	-0.00368***	(0.000968)	-0.00270	(0.00342)
repaycap	-0.00481	(0.0149)	-0.0452	(0.0247)
fibal	-0.000686	(0.00408)	-0.00519	(0.0627)
opmargin	0.00133	(0.00658)	-0.0219	(0.0186)
avgap_ofc	0.0104	(0.0111)	0.0180	(0.0329)
avgap_opmargin	-0.00157	(0.0185)	0.0233	(0.0781)
constant	3.669***	(0.956)	7.570***	(1.842)
N	156		48	
$\boldsymbol{R^2}$	0.589		0.734	

Table 3. Regression results.

Robust standard errors in parentheses
*Precision level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$*

The coefficients of the crowdlending campaign-specific variables exhibit less expected impacts. On the one hand, an increase in the duration of the auction process and/or in the number of lenders may induce higher competition among sellers, and in turn, induce a decrease in interest rate, all things being equal. On the other hand, an increase in the duration of the auction process may discourage some lenders from bidding for that project since the feedback on their bid will be delayed which will delay the loan start date should their offer be accepted. Our results show a non-linear effect (inverse U shaped relationship). However, we should stress that we are observing only the post-campaign number of lenders (i.e. the lenders selected by the borrower after the auction process ended). Therefore, we are not able to assess the magnitude of the selection process (i.e. the ratio between the ex-ante and ex post numbers of bidders). Also, we cannot control for the amount of the average bid. For these reasons, we use these variables only as control variables.

Unilend ratings exhibit the expected impact of a higher rating resulting in a lower interest rate. The magnitude of this effect is interesting: one additional “star” (i.e. point) results in a 0.46 percentage point saving on nominal interest rates. However, it should be noted that none of the financial ratios or indicators, whether borrower- or sector-specific has a significant impact on the interest rate. This conclusion is robust to many alternative specifications. For example, we used alternative financial indicators and were unable to detect any significant effects. We replaced the operating profit margin or financial balance ratios by the repayment capacity ratio to account for the borrower's financial strength. Similarly, we used the ratio of the overall gross margin instead of the operating profit margin, and the impact of the interest rate on turnover was used to substitute for the financial balance ratio.

In addition, there may be some multi-collinearity among the explanatory variables e.g. among the Unilend rating and the financial variables. To check this, we ran alternative regressions where we dropped the Unilend rating. We were unable to infer a significant (with a minimum 10% precision level) relationship between the financial variables and the interest rate.

We also used sector-specific variables. We introduced these explanatory variables either as independent variables (*avgap_ofc* and *avgap_opmargin*), or as new variables measuring the gap between the borrower's and the sector's ratio. In both cases, we were unable to identify any significant effect.

Finally, we introduced the borrower's AFDCC rating[8], as explanatory variables - both with and without the other financial variables. Introducing the AFDCC rating affects only the significance of *rtUnilend* score. It might be that Unilend uses some part of the AFDCC score in its own rankings, although the coefficient of the AFDCC rating is never statistically (<10% precision level) significant.

There are two possible explanations for the weak impact of the financial variables on the interest rate level. On the one hand, these ratios can be computed using data from the borrower's balance sheet and profit and loss accounts, and these data are available on the Unilend platform. Therefore, we can hypothesize that lenders face either time or cognitive restrictions to inferring information from these data. On the other hand, we can conjecture that bidders rely heavily on the Unilend rating which they perceive as a credible and synthetic measure of project quality since bidders delegate authority to Unilend. This does not exclude other plausible explanations. For instance, it could be conjectured that some bidders are characterized by low levels of risk aversion and/or are interested in the fun aspects of the auction mechanism. Finally, we cannot exclude herding behavior. Such behavior is common among agents to deal with uncertainty, and are discussed in Herzenstein et al. (2011) in the context of the Prosper P2P lending platform. To explore this aspect in more detail would require less aggregated data. However, anecdotal evidence from observation of the Crowdlending.fr discussion forum, and other dedicated platforms, suggests that these platforms help agents to coordinate over risk assessment. These forums are likely to enhance mimetic behaviors. Nevertheless, the lack of correlation between interest rates and financial ratios is a preoccupying result. As a matter of fact, Emekter et al. (2015) found that credit grade, debt-to-income ratio, FICO score (an equivalent of the French AFDCC rating) and revolving line utilization play an important role in loan defaults.

4.2 After Autolend introduction

To assess the impact of the introduction of Autolend on interest rates, we performed another regression using observations on projects where Autolend was available. The results are presented in Column (b) table (3) and should be compared with the results in column (a). After Autolend was introduced, the Unilend score becomes the unique significant explanatory variable. Loan duration and loan size have no impact. Similarly, neither the duration of the Crowdlending campaign nor the number of lenders has any impact on the interest rate. By introducing deterministic lending rules, introduction of Autolend changes these two explanatory variables and thus, their impact on the interest rate level.

The magnitude of the Unilend ranking coefficient also increases (-1.159 vs. -0.469). This suggests that the Autolend mechanism induces lenders to rely more (compared to the prior Autolend situation) on the Unilend ranking. However, note that the degree of significance of this coefficient is lower – most likely caused by the difference in the two sample sizes.

[8] French Companies' Credit score measured by the Association Française des Credit Managers et Conseils (AFDCC).

Overall, it seems that the introduction of Autolend has had a strong impact on bidding behavior. First, it led to an increase in the role of the Autolend ranking. Second, those behaviors are less easy to explain using the previous set of variables. However, this result needs to be balanced. On the one hand, the introduction of Autolend is relatively recent, and so the sample size is restricted. Second, a few months after Autolend was implemented, Unilend introduced price ceiling and price floor constraints on bidders.

4.3 Policy implications

Our results highlight the tendency of the crowd to use financial ratings as a support decision artefact and moreover, the tendency to use lending robots as a substitute decision artefact. These results raise the question of the financial literacy of the households and their ability to evaluate financial risks. The level of financial education of the French population itself is considered to be very low in comparison to other countries (International Allianz Pension Papers 1/2017). In addition, the disparity of accounting information of small businesses can increase the risks of informational asymmetry. In accordance with the work of Franks et al. (2016), substitution between the lenders and the platform in the information processing and the tendency of the lenders to use heuristic simplifications would not generate any problem of consistency since the rating provided by the platform involves an unbiased and sufficiently granular degree of discrimination among projects. However, according to Bellefamme et al. (2015), crowdlending platforms could be encouraged to hide part of their private information in order to preserve the attractiveness of potential borrowers. According to Serrano-Cinca and al. (2015), use of a proprietary algorithm is more expensive for a platform than relying on an outsourced rating. Insofar the role of the rating is crucial in the lending process and also in the Autolend pre-settings. Therefore, a natural extension to this study is to analyse the predictive power of the rating on a P2B lending platform. In that sense, there is a need to investigate the opportunity to extend the current regulatory framework of credit rating agencies (Directive 2013/14/EU in the European Union) to proprietary credit rating of lending platforms since this regulation seeks to reduce conflicts of interest and make agencies more accountable and transparent for their actions. Similarly, actual financial market regulation may also be transposed to crowdlending platforms. For instance, recent regulatory initiatives concerning algorithmic trading on financial markets such as Markets in Financial Instruments Directive 2 (MIFID2). MIFID2 ensures that a firm engaging in proprietary algorithmic trading cannot be used for any purpose that is contrary to market fairness. To implement this objective, the directive requires a firm to provide details of the controls and systems and, in relation to decision support systems, a description of the strategies. Development of crowdlending platforms and of lending robots raises similar regulatory issues.

5 Conclusion

This paper has analyzed the impact of introducing a computerized decision support system (i.e. a robot advisor) on the price setting mechanism and outcome of an online crowdlending platform. We considered a leading French crowdlending platform which introduced this type of robot (Autolend) in the context of an auction-based price-setting mechanism. Autolend enables bidders (lenders) to adjust bids automatically (proxy bidding). It also helps them to set a bid specific to the characteristics of the project/borrower. We contrasted the situations before and after the introduction of Autolend. Prior to the introduction of Autolend, we found that the level of (nominal) interest rates was correlated significantly to project-specific characteristics such as loan size and loan duration. We found that lenders seem to give weights to information that is straightforward to process, and rely on the platform to process more complex information (e.g. financial ratios and indicators). On the one hand, despite this information being accessible from the platform's website, various financial indicators do not influence the interest rate level. In contrast, the project's ranking available on the platform has a significant influence. We can infer that users (i.e. lenders) give priority to synthetic and non-expert information (Unilend rating) rather than investing time and cognitive resources in computing their own financial ratios.

As the number of per project lenders shows, Autolend seems to have met users' expectations. The influence of the platform's rating and the computerized decision support system seems to have been magnified. That is, implementation of Autolend seems to reinforce the weight attached by the crowd to the platform's scoring. We can consider lenders to be a heterogeneous population mixing experts (financial analysts, etc.) with inexpert bidders. In the case of high skilled agents, it would seem plausible that the sudden acceleration of the auction process –duration of the auction process fell by 75% after implementation of Autolend–prevented them from processing the information on their own since this takes time, and risks the target being reached before they come to a decision. If this hypothesis were confirmed, it would mean that the introduction of computerized decision support has an influence also on those agents that may not (initially) be willing to use it.

One possible issue is learning. In the current version of this paper, we distinguished two subperiods (before and after Autolend introduction) tough the first subperiod has a relatively long duration. It is characterized by the introduction of the Unilend platform, and more generally of crowdlending platforms in France. Therefore, we could expect agents (lenders, borrowers) to have learned about the implementation of the platform and about the efficiency of their bidding and lending strategies. Though, since average level of interest rates in France has changed over the whole period, there is also a need to control for that. The same issue arises post-Autolend introduction. In a future version of this work, we will include both issues both as robustness checks and to investigate the potential effects of learning.

This argument provides support for an observed trend in the crowdlending industry i.e. a switch from an auction based price setting mechanism (with a high latitude for agents to set their price) to a constrained or fixed price setting mechanism based on a computerized decision support system (which gives less latitude to users). If such a trend were confirmed, it would suggest some equivalence between the crowdlending and B2C e-commerce industries: many players in the B2C e-commerce industry started by employing auction-based business models (e.g. EBay in the US and EU). While these price-setting mechanisms still exist, they are becoming less widespread and popular. This switch has been attributed to the characteristics of auction based price setting mechanisms. These mechanisms may exhibit some "fun" features. However, those benefits seem transitory compared to the long-lasting transaction costs; bidders need to monitor the bids of other bidders in order to adjust their bidding strategies. In the case of the crowdlending industry, there is an opportunity cost associated to delayed financial investment. These types of arguments may be invoked by crowdlending platforms when designing their platforms' rules. Our analysis suggests that changing the rules (i.e. introducing computerized design support) is far from neutral for bidders' strategies and outcomes.

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Appendix

Appendix 1. Robustness checks (all sample) [Standard errors in parentheses ; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$]

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	avintrate	avintrate	avintrate	avintrate	avintrate	avintrate	avintrate	avintrate
duration	0.130***	0.137***	0.128***	0.125***	0.121***	0.125***	0.123***	0.133***
	(0.0223)	(0.0238)	(0.0170)	(0.0235)	(0.0234)	(0.0235)	(0.0231)	(0.0232)
Duration x duration	-0.00104***	-0.00109***	-0.00104***	-0.000954**	-0.000927**	-0.000954**	-0.000976**	-0.00108***
	(0.000285)	(0.000299)	(0.000215)	(0.000295)	(0.000295)	(0.000295)	(0.000299)	(0.000301)
auction_time x auction_time	-0.00246**	-0.00239*	-0.00302***	-0.00279**	-0.00281**	-0.00279**	-0.00244*	-0.00212*
	(0.000907)	(0.000931)	(0.000719)	(0.000918)	(0.000915)	(0.000918)	(0.000961)	(0.000969)
auction_time	0.0897**	0.0856*	0.134***	0.101**	0.104**	0.101**	0.0962**	0.0794*
	(0.0342)	(0.0350)	(0.0274)	(0.0345)	(0.0345)	(0.0345)	(0.0360)	(0.0360)
lendersnb	-0.000743*	-0.000677*	-0.000868***	-0.000693*	-0.000733*	-0.000693*	-0.000758*	-0.000709*
	(0.000315)	(0.000325)	(0.000245)	(0.000318)	(0.000322)	(0.000318)	(0.000338)	(0.000343)
principal	0.0119***	0.0117***	0.0100***	0.0124***	0.0125***	0.0124***	0.0124***	0.0123***
	(0.00294)	(0.00300)	(0.00220)	(0.00294)	(0.00295)	(0.00294)	(0.00316)	(0.00321)
autolend	-0.788**	-0.853**	-0.159	-0.831**	-0.786**	-0.831**	-0.686*	-0.761*
	(0.273)	(0.282)	(0.202)	(0.275)	(0.276)	(0.275)	(0.298)	(0.302)
repaycap	-0.00218	-0.00436		-0.00717	-0.00364	-0.00717		
	(0.0109)	(0.0113)		(0.0111)	(0.0109)	(0.0111)		
opmargin	-0.00149	-0.00212		-0.00115	-0.000274	-0.00115		
	(0.00606)	(0.00620)		(0.00606)	(0.00614)	(0.00606)		
fibal	-0.000256	-0.000254		0.000735	0.000426	0.000735		
	(0.00422)	(0.00427)		(0.00418)	(0.00422)	(0.00418)		
tu_m_refy	-0.0302	-0.0269	-0.0315	-0.0253	-0.0308	-0.0253	-0.0240	-0.0303
	(0.0237)	(0.0250)	(0.0221)	(0.0244)	(0.0242)	(0.0244)	(0.0254)	(0.0257)
avgap_ocf		-0.00278		0.00137		0.00137		
		(0.0185)		(0.0181)		(0.0181)		
avgap_opmargin		0.0139		0.0166		0.0166		
		(0.0101)		(0.00987)		(0.00987)		
rtUnilend			-0.630***	-0.498**	-0.457**	-0.498**	-0.438*	
			(0.126)	(0.156)	(0.156)	(0.156)	(0.172)	
sect_ocf					-0.00852			
					(0.0241)			
sect_opmargin					0.00271			
					(0.0195)			
AFDCC_rating							-0.00489	-0.0198
							(0.0244)	(0.0240)
_cons	3.640***	3.500***	5.605***	5.227***	5.269***	5.227***	5.159***	3.746***
	(0.493)	(0.524)	(0.559)	(0.746)	(0.750)	(0.746)	(0.769)	(0.542)
N	209	204	334	204	205	204	173	173
R^2	0.684	0.676	0.652	0.693	0.689	0.693	0.694	0.682
adj. R^2	0.666	0.654	0.642	0.670	0.666	0.670	0.675	0.664