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Bids for Speed: An empirical Study of Investment Strategy Automation in a Peer-to-Business Lending Platform

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We investigate how introducing a bidding agent impacts the process and outcome of an online reverse auction in the context of a crowdlending platform. We consider this issue in the context of a peer-to-business platform that connects individual lenders to small and medium-sized enterprises. Using a before/after study design, we perform an econometric analysis and find that introducing a bidding agent had a positive and dramatic impact on the number of bids and bidders and reduced the time necessary to collect the funds. For projects with lower ratings, it also positively impacted the number of lenders and indirectly enhanced portfolio diversification. We find that after the bidding agent was introduced, well-rated projects benefited from lower interest rates, the magnitude of the change depending positively on their rating. These results provide evidence that the bidding agent generates savings in the screening and bidding costs incurred by lenders and benefits both sides of the platform. Our contribution documents the role of bidding agent as a strategic tool to enhance financial intermediation. It also sheds light on how two types of decision support systems (rating-based and bidding agent) interact and shows that this interaction is of crucial importance with respect to the financial regulation of platforms if the crowd has low financial literacy.

Keywords: decision support system; crowdlending; bidding agent; online reverse auction.

1. Introduction

The irruption of FinTech, financial technologies based on novel business models and information systems (IS), in the mid-2010s has profoundly reshaped the banking and finance industries. Crowdfunding services are examples of this trend as they connect investors (known as "the crowd") to borrowers without use of a banking intermediary. Crowdlending is a specific type of crowdfunding which connects lenders (typically individual lenders) to borrowers. The crowdlending industry can be segmented into loans to individuals (consumer or student loans, known as peer-to-peer [P2P] Lending), real estate loans and Small and Medium-sized Enterprise (SME) loans (known as peer-to-business [P2B] Lending).[3] Crowdlending platforms are two-sided markets [40] and the lending process is a tripartite

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[3] "Global Peer to Peer Lending Market Competition, Forecast & Opportunities, 2024" 2019 Report. Available at [https://www.alliedmarketresearch.com/peer-to-peer-lending-market], last retrieved on December 9 2021.

interaction between the two sides (lenders and borrowers) and the platform. Objectives may diverge and information systems can play a moderating and strategic role (in the sense of [35]) to help convergence.

In this paper, we consider a platform that uses two types of strategic IS: Transaction Processing Systems (TPSs), software that facilitates the trading process; and Decision Support Systems (DSSs), software provided to lenders to assist their investment decisions. With respect to P2B lending, a TPS can be built either on a fixed-price principle (i.e., the interest rate is defined by the platform before the campaign starts) or an Online Reverse Auction (ORA), where the interest rate level is determined by the crowd through a bidding process. Such auctions are able to attract lenders because they enable personalized pricing [38], since each lender can set a specific interest rate. Yet they also generate additional costs (i.e., screening and bidding costs) for lenders. For that reason, many auction-based crowdlending platforms have implemented bidding agents (BA) to mitigate these costs. Therefore, the result of the bidding process – and hence interest rate determination and portfolio allocation – relies increasingly on the automation of investment decisions [28].

How the introduction of a BA impacts behaviors and outcomes is a relatively unexplored issue in the academic literature dedicated to crowdlending and this study aims to add to the existing literature. Most papers in this body of literature focus on one of the two sides of the market: either lenders' decisions [8, 23, 24, 38, 51] or borrowers' strategies, by investigating which campaign characteristics are factors of success [18, 32, 43]. In this paper, we investigate the impact of introducing a BA into an existing ORA-based TPS. To the best of our knowledge, only three papers have specifically studied the role of a BA on the intermediation process between lenders and borrowers on a crowdlending platform. In the case of P2P platforms, [6] studied the effects of introducing a BA into the revelation of market information. [14] analyzed the impact of a BA on lenders' behavior, their return on investment, and the overall efficiency of a P2P lending platform in China. [16] investigated the price discovery process in the context of a P2B platform. While financial issues remained the primary focus of this last study, it incorporated an analysis of the impact of a BA on informational efficiency. In these three papers, lenders had the opportunity to use a BA for the whole study period.

In our paper, we collected data from Unilend, an ORA-based platform which pioneered P2B lending in France in 2013 and introduced a BA (Autolend) in 2016. This provided an interesting before/after context to investigate the impact of automation through the introduction of a BA in the context of a P2B platform. We find that this BA had a positive impact on the number of bids and bidders in the auction and also reduced the time necessary to collect funds. In this sense, introducing the BA improved the general efficiency of the auction process by lowering transaction costs. It also impacted the level of interest rates. However, we find that this impact was mediated by the rating given to the project by the platform: after the BA was introduced, well-rated projects benefited from an extra saving on interest rates. Section 2 surveys the existing literature. Section 3 presents the data and research hypotheses. Section 4 elaborates on hypothesis testing and presents the results, which are discussed in Section 5. Section 6 concludes.

2. Literature review

2.1. Systematic Review of IS research on Crowdfunding

The FinTech evolution has attracted much academic attention in the fields of IS [21]. Nevertheless, P2B lending remains relatively little studied. Following the methodology of [9], we conducted a systematic search to identify articles on crowdfunding. We considered publications in the thirteen top IS journals[4] over the period 2010-2021 (*see supplementary material*). We were thus able to identify 73 articles and classified them according to the category of crowdfunding they considered (Table 1).

Reward	**Equity**	**Donation**	**Lending**			**Others**
			P2P	**P2B**	Real Estate	
40	3	6	19	**1**	1	3

Table 1. IS research in crowdfunding sorted by category.

[4] Decision Support Systems, European Journal of Information Systems, Expert Systems with Applications, IEEE series, Information and Management, Information Systems Journal, Information Systems Research, Information Technology & People, Journal of the Association for Information Systems, Journal of Strategic Information Systems, Journal of Information Technology and MIS Quarterly.

We can observe that most IS research is dedicated to reward-based platforms (40 papers). Even if lending-based platforms are the second most important topic (21 papers), the great majority of those papers are focused on P2P lending (between individual borrowers and individual lenders, 19 papers). Only one study addresses real estate lending and one, lending specifically to SMEs. Regardless of the type of the platform, 51 papers are dedicated to backers' behaviors (social interactions, information acquisition and/or funding decisions), 13 papers are dedicated to fundraising determinants (success and performance) and 21 papers study the whole process, that is, the coordination between users, the influence of the market design, and the links between campaign characteristics and outcomes (success/failure). Finally, only nine papers are dedicated to the role of DSSs. All of them without exception focus more on the design of a DSS than on its impacts. The impact of fundraising automation therefore remains a relatively unexplored topic within academic research in information systems management (MIS).

2.2. Theoretical background & related research

Automation of financial decisions encompasses several issues in the fields of economics, finance and MIS. To disentangle those issues, we first emphasize the specificities of decisions in the context of auction processes and financial decisions (2.2.1). Second, we consider the IS literature focusing on the specific DSS used in ORA crowdlending contexts (2.2.2). Based on the literature, we then identify the various impacts of introducing a BA, to develop the background for our research hypotheses (2.2.3).

2.2.1. Auctions, crowdlending and financial decisions

There is a wide theoretical and empirical literature documenting behaviors in digital auctions. Focusing on the benefits and costs of auction processes in a digital context, several arguments may justify the use of auctions. First, [13] argued that ORAs can increase the opportunity of obtaining more attractive prices for a buyer and improve market transparency by revealing market valuation for the supplier. In the same vein, [46] showed that if the value of an object is uncertain (such as financial assets), auctions are typically preferred to posted prices. Second, [37] highlighted that some users draw utility ("*shopping entertainment*") from participating in an auction and enjoy a better user experience, in particular the enjoyment of winning ([12]). They can also benefit from other positive effects: the ability to monitor and obtain a personalized price, and the opportunity to herd, learn from or beat the crowd ([14], [22], [51]). However, auctions also generate additional costs, such as bidding costs (see 2.2.3) since a bidder needs to monitor the auction and repeatedly post bids ([27]). For instance, [3] negatively linked the consumer surplus with auction duration and competition (generating an increase in bidding costs).

Compared to auctions in e-commerce contexts, auctions in a crowdlending context are distinctive in that they entail a credit relationship. In a credit relationship, the lender has to make the best possible estimate of the quality of the borrower, that is, the probability of default, and this relationship is characterized by high information asymmetry, which generates a screening cost incurred by lenders [15, 42]. Information asymmetry is exacerbated in the context of business loans since financial information is complex and mitigating information asymmetry requires the lender to exhibit high financial literacy [39]. [33] have shown that the rates observed on lending platforms can deviate from fundamental credit risk analysis because of the crowd's lack of expertise. In the case of lending platforms, [22, 47, 48] showed that extra-financial variables (soft information) can influence the outcome of ORAs because hard information, derived from the accounting data produced by SMEs, requires strong financial skills to be correctly assessed. Therefore, analysis of SME projects requires computing a lot of information and solving such a complex problem under uncertainty often relies on a limited number of simplifying heuristics [45].

2.2.2. DSSs used in crowdlending platforms

Crowdlending platforms are particularly suited to the introduction of DSSs in the form of trading agents [20]. [19 p:252] defined trading agents as algorithms that "*enable automated acquisition of information and data processing to provide investment proposals with little or no human intervention based on pre-defined parameters based on customers' investment goals, financial background and aversion to risk.*" These agents enable savings on transaction and information-processing costs ([38]) and can help lenders to set an acceptable risk-return-ratio with as little wasted time as possible. Two types of DSS may be distinguished in this context. The first and most widespread DSS in the crowdlending business are rating-based models, which assign a credit or profit score to each loan. Those scores may derive from statistical methods or artificial intelligence approaches [1, 4, 29, 41]. The rating algorithm is often a proprietary one: its source code is closed and only general information about how the rating is processed is provided to lenders. This is the case for the Unilend platform analyzed in this study. In addition to ratings, some platforms may also provide recommendation systems that match loans according to lenders' motivations [50]. This kind of DSS is typically able to support the human decision by providing simplified signals. However, it cannot fully replace it. A second type of DSS is a trading agent that can both collect and classify available data and execute orders. In the particular context of ORAs, trading agents are called bidding agents. The BA usually computes information and chooses the bidding strategy on behalf of users according to their parametrization [20] and it is usually specifically designed to replace human decisions. [11] proposed a classification of three types of BA: the simple type, which only notifies a user about current bid status (beaten or not); the intermediary type, which generates automatic bids based only on a single parameter; and the advanced type, which includes more decision parameters and the potential to automatically bid in new auctions.

2.2.3. Impacts of introducing a BA in an ORA crowdlending context

In an ORA context, a lender decision has to be decomposed into two steps (formulation and implementation of the investment strategy) and specific costs are associated with decision-making at each step. Before the BA was introduced, bidders first needed to invest time to analyze the opportunities and risks associated with each project in order to eventually select projects in which to invest. This involved an effort by the lender to compute hard and soft information and to assess risk as well as possible. The cost of this effort was mostly an opportunity cost associated with time use and would vary according to, for example, the lender's individual expertise. Second, once bidders had entered the auction process, they needed to monitor the auction (i.e., look at the bids of other participants, check the status of their bids and submit new bids). Thus, considering time constraints, implementation of the bidding strategy involved another effort that generated opportunity costs. To depict those costs, we refer hereafter to "screening costs" (step 1) and "bidding costs" (step 2).[5]

The introduction of a BA impacts on those costs. At the first step, a BA is often coupled with a rating-based DSS in order to provide tools to sort projects according to various criteria and automate formulation of the investment strategy depending on pre-defined criteria [38]. The ultimate impact on screening costs is not easy to predict since those users with low financial literacy and expertise may experience a large reduction in screening costs because their ability to process complex information is low. On the contrary, expert users may lose from the use of the bidding agent because their ability to process information is high and their screening costs are low. Also, manual bidders (i.e., the bidders who do not use the BA) can typically use dedicated discussion forums that provide opportunities to learn through talk and observation at that stage [49]. Therefore, since use of the BA excludes the possibility of integrating any qualitative and extra-financial information in the formulation of their strategy, those agents may face a loss in accuracy by relying only on the rating-based DSS provided by the platform.

At the second step, the BA provides proxy bidding to its users. Proxy bidding enables the implementation of bidding strategy to be fully automated by automatically generating a new bid whenever a bid is beaten until a user-predefined reservation criterion is met. Therefore, the need to monitor the auction vanishes and so do bidding costs. This may in turn increase the probability to win the auction and the enjoyment of bidding in the case of a "smart bidder" profile ("*the less effort, the more positive the affect*", [27]). However, other indirect effects may counterbalance this decrease in bidding costs. Indeed, during the auction process, automated bids exclude any possibility of rational herding and bidders observing the "wisdom of the crowd" in their positioning [16, 51]. Also, using a BA lowers the enjoyment of bidding for an "active bidder's" profile ("*the more effort invested, the more positive the affect*", [27]) since this type of bidder experiences a positive affect by exerting an effort with manual bidding to win the game.

[5] Depending on the literature, many different labels have been used to represent closely related costs (e.g., search costs, transaction costs, decision-making costs). Since those concepts may not exactly reflect the specific costs incurred in an ORA process, we prefer to refer to screening and bidding costs in the context of our study.

Therefore, the literature on BAs sheds light on differential effects associated with introducing a BA. As both screening and bidding costs decrease, we may expect the BA to increase ORA attractiveness and enhance portfolio diversification. However, as evidenced by empirical research, the crowd is heterogeneous concerning the use of automated investment advisory processes ([25]) and variations of screening and bidding costs are heterogeneous among lenders because they depend on their characteristics. This makes the prediction of ultimate impacts on the entire crowd more complex. Based on this literature, we formulate two series of research hypotheses.

3. Data

3.1. Study Context

Unilend was the pioneer crowdlending platform specializing in loans to SMEs in France. It began operations in 2013 and was acquired by a competitor (PretUp) on October 17, 2018.[6] During that period, the platform raised a total of almost 33 million euros. Borrowers are located in France and belong to a wide variety of sectors. Various loan projects can be accepted, including cash refinancing and intangible asset financing projects but excluding real estate acquisitions and loan repurchases. To be eligible, SMEs have to prove they have been operating for at least three years. Loans are repayable over a 3- to 60-month term, and the loan target covers amounts from €10,000 to €500,000. For each new project submitted to the platform, Unilend performs a credit risk analysis and displays it in the form of a rating from 1 to 5 points.[7] Only projects that receive a minimum 3-point rating can enter the lending process and are posted online. In this case, the platform and the borrower together set a deadline (maximum duration of the auction process). For each project, the campaign is presented on a single webpage that displays hard and soft information (campaign characteristics, project- and company-

[6] This purchase was highly unexpected so it could not affect user decisions in our data. The platform was first closed and then reopened. Since, reopening of the platform might have produced unobservable changes, we restrict our analysis to pre-acquisition observations.

[7] This rating is the output of an in-house (not publicly disclosed) algorithm that processes economic and accounting data. The acceptance/rejection of the project is determined by this appraisal.

specific information including the financial accounts with the key figures from the borrower's financial statement) to all potential bidders. The campaign starts immediately once it is posted online, as does the ORA-based funding process. Beginning April 19, 2016, Unilend offered lenders the option to activate Autolend, a BA that can automate auction bids.

Bidding rules. The auction process on the platform can be described as follows. Bids include a ticket size (i.e., the amount that an individual lender is willing to lend) and an interest rate. The ticket size has to range from €20 to €2000.[8] Interest rates have to be within the ceiling and floor values defined by the platform (see *infra*). Once a bid is submitted, it is posted online and bidders can observe how their bids compare to other bids. They can also observe how much of the total loan amount has already been collected. Lenders can update bids at any time during the campaign. When the loan target is met, the borrower selects the most competitive bids. We refer to the time that elapses between the campaign start and the time the loan target is met as the target duration.

If the financial target is met before the deadline, borrowers have the choice to continue the auction process in order to benefit from a lower average interest rate. They can decide to close the auction at any time until the deadline is reached. We define the post-target duration as the time that elapses between the time the target is first reached and the closing time. Figure 1 depicts the whole sequence of the campaign progress. After the auction process ends, conditional on the financial target being met, the borrower has five days to accept or refuse it. If it is accepted, the loan is issued and the loan size amounts to the campaign loan target.[9]

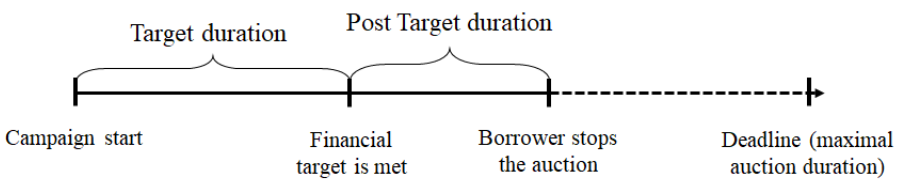

Figure 1. Campaign progress

[8] This upper bound has a legal origin (French 2014 Crowdlending Regulation).
[9] If the financial target is not met, the whole campaign is canceled.

Bidding process before and after introduction of Autolend. Before 2016, bidders could only submit bids manually. For each project, they had to formulate their investment strategy (i.e. decide to invest or not, and if so define ticket size and reservation rate) and then to implement it (i.e. manually submit bids). After 2016, they had the opportunity to activate Autolend. The bidding agent Autolend. Autolend not only automates bidding strategy but also investment strategy: when a bidder activates it, it devotes some cash amount to be automatically invested in new projects that appear on the platform.

There are two versions of Autolend (simple vs. advanced modes). In the simple mode of Autolend, bidders have to set the amount per project they wish to lend, and a single reservation interest rate. When bidders decide to activate Autolend advanced mode, they have to fill a double-entry table that defines all the reservation interest rates they choose. Figure 2 shows a screenshot of this double-entry table depending on loan duration (in rows) and Unilend rating (in columns) as displayed on Unilend's website. Using the advanced mode, bidders can decide not to bid on specific loan duration and rating combinations (in this case the plus sign appears in the box). Thus, the only difference between the advanced and simple modes is the ability for bidders to discriminate among projects based on their duration and rating. In both cases, note that the bidding strategy applies to every new project and lenders do not have to parametrize Autolend every time a new project appears on the platform. It cannot be changed while an auction process is ongoing, however, the table can be freely modified for subsequent auctions. It worth noting that bidders can still submit manual bids as described above, whether they use Autolend or not.

	●●●○○	●●●◐○	●●●●○	●●●●◐	●●●●●
3 to 12 months	7,0%	6,0%	4,5%	+	3,5%
18 to 24 months	7,5%	6,5%	5,0%	4,5%	3,5%
36 months	8,5%	7,0%	6,0%	4,5%	4,0%
48 months	9,0%	7,5%	6,5%	5,0%	4,5%
60 months	+	7,5%	6,5%	5,5%	4,5%

Figure 2. Double-entry table to be filled by lenders using Autolend (advanced mode)

Changes in ceiling and floor interest rates. In addition to the introduction of Autolend, two other events are worth noting. When Unilend started operations, auctions started at 10% (ceiling interest rate) and bids were allowed to decrease to 4% (floor interest rate). These two rates were the same for all projects, independent of the characteristics and rating of the project. Unilend has since adjusted these floor and ceiling rates twice. The first change took place on August 25, 2016, and the second one on November 6, 2017. In 2016, Unilend introduced a grid of floor and ceiling interest rates, depending on the loan duration and rating. In 2017, Unilend released a new version of this grid in which some rates were updated.

Figure 3 shows those two grids based on screenshots of the Unilend website at that time. In general, we observe from the comparison of these grids that ceiling interest rates were decreased in 2016 and floor interest rates were adjusted, with large increases for some ranking and duration combinations. In terms of magnitude, the changes introduced in November, 2017 were less substantial than those of August, 2016. Note that the underlying TPS used by Unilend did not change, only its parametrization did. We will further control for these changes by considering two separate dummy variables (*grid1* and *grid2*).

From 12/6/2013 to 8/25/2016	∀ loan duration & rating	4,0%	10,0%								
From 8/25/2016 to 11/6/2017		★★★☆☆		★★★½☆		★★★★☆		★★★★½		★★★★★	
	3 à 12 mois	6,0%	8,5%	5,0%	7,0%	4,0%	5,5%	3,5%	4,5%	3,5%	4,5%
	18 à 24 mois	7,0%	10,0%	5,5%	8,0%	4,5%	7,0%	4,0%	6,0%	4,0%	5,5%
	36 mois	8,0%	10,0%	6,5%	9,0%	5,5%	7,5%	4,5%	6,0%		
	48 à 60 mois	8,5%	10,0%	7,0%	10,0%	6,0%	8,5%	5,0%	7,5%	4,5%	7,0%
Since 11/6/2017		○○○		○○○(		○○○○		○○○○(		○○○○○	
	3 à 12 mois	6,3%	8,0%	5,3%	7,0%	4,0%	5,3%	3,5%	4,5%	3,0%	4,0%
	18 à 24 mois	7,0%	8,7%	5,8%	7,5%	4,5%	6,0%	4,0%	5,0%	3,3%	4,3%
	36 mois	7,8%	9,5%	6,3%	8,0%	5,5%	7,0%	4,3%	5,5%	3,7%	4,7%
	48 mois	8,3%	9,7%	6,8%	8,5%	5,8%	7,5%	4,5%	6,0%	4,0%	5,0%
	60 mois	8,5%	9,9%	7,0%	8,7%	6,0%	7,7%	4,8%	6,3%	4,3%	5,3%

Figure 3. Floor and ceiling interest rates set by the Unilend platform

3.2. Data collection

We collected exhaustive data about publicly available projects on the Unilend platform from December 6, 2013, to September 25, 2018. Over the period, 463 projects tried to raise funds, of which 451 were successful.[10] We focus on those projects and for each project, we consider the following set of information at the time of the crowdlending campaign: bidding process and outcome information (these data are measured after the auction process occurred), campaign characteristics, company specific information (sector and financial information[11]) and macroeconomic[12] and time indicators. In some analyses, the number of observations was reduced to 385 because of missing data.[13] Table 1 defines the set of variables used in the quantitative analysis.

[10] Only 12 projects did not meet their target. One project was excluded from the platform because the company launched a similar campaign on another platform. The other 11 projects failed to gather the requested loan target, 9 before Autolend was introduced and 2 after. These 11 projects were characterized by high loan target and low rating.

[11] The simplified income statement and balance sheet displayed on the Unilend website provides various accounting raw data (e.g., EBIT, debt) from the most recent fiscal year before the campaign.

[12] We extracted from Bloomberg database the rate of return of French Treasury Bonds with a 36-month duration to control for variations of the interest-rate level in the economy. We chose 36-month duration since is the closest one to the average project duration on Unilend (40.82 months).

[13] The company turnover for the previous year or two was occasionally missing, notably for recent companies but also if data from previous fiscal year were not provided.

Variable name	**Variable description**	**Variable type**
Dependent variables		
interestRate	Average interest rate (as a percentage)	Bidding outcome
nbBidders	Absolute number of bidders / *loanTarget*	Bidding process
nbBids	Absolute number of bids / *loanTarget*	Bidding process
nbLenders	Absolute number of lenders / *loanTarget*	Bidding outcome
postTargetDuration	Time elapsed between the loan target is first met and the end of the auction (in days)	Bidding process
targetDuration	Time necessary to reach the loan target (in days)	Bidding process
Variables of interest		
autolend	=1 after Autolend's introduction; 0 before	Campaign characteristic
loanDuration	Loan duration (in months)	Campaign characteristic
rating	Rating set by the platform (0-2 scale)	Campaign characteristic
General Control variables		
36mTBonds	Rate of return of French 36-month Treasury Bonds, 7-day average before campaign starts	Macroeconomic indicator
commerce, construc, hotrest, indagr, oserv	=1 if borrowers belong to the commerce, construction, hostel & catering, industrial or agricultural, other services sector, respectively; 0 otherwise	Company specific information
grid1	=1 if grid1 is in force (i.e., between August 25, 2016 and November 6, 2017; 0 otherwise)	Campaign characteristic
grid2	=1 after grid2 is in force (i.e., after November 6, 2017); 0 otherwise)	Campaign characteristic
loanTarget	Amount of the loan requested by the company (in thousands of euros)	Campaign characteristic
loanTargetlog	Natural logarithm of *loanTarget*	Campaign characteristic
nbproj	Number of other projects available three days prior to the campaign starting on the platform	Campaign characteristic
serial	=1 if the company launched at least one campaign or more through the platform previously; 0 otherwise	Campaign characteristic
time	number of days elapsed since December 6, 2013	Time indicator
turnover	Firm's turnover (in millions of euros)	Company specific information
Financial Control variables		
debt, liq, prof, struct	Liquidity ratio, structure ratio, indebtedness ratio, profitability ratio	Company specific information
rgDebt, rgEBIT, rgTurn	Year-to-year growth rate of the company's debt, EBIT and turnover	Company specific information
gDebt, gEBIT, gTurn	= 1 if the year-to-year growth rate of the company's debt, EBIT and turnover, respectively, are positive; 0 otherwise	Company specific information

Table 1. Variable definition

3.3. Research hypotheses and variable measurement

As was discussed in Section 2.2.3, introducing a BA can have differential effects on the screening and bidding costs of individual lenders depending on their characteristics. For this reason, the impact of introducing a BA on the bidding behavior of the whole crowd is not deterministic. In relation to Autolend, we formulate here two series of hypotheses based on two general assumptions that distinguish impact on the bidding process (Assumption A) and on the bidding outcome (Assumption B).

Assumption A. Autolend impacts the bidding process.

High bidding and screening costs are associated with manual bidding in an ORA. Autolend enables auction automation. Indeed, the BA allows for permanent monitoring in order not to miss any project. It allows participation in multiple auctions simultaneously and exhibits large algorithmic calculation capabilities. [14] and [27] also demonstrated that a BA is likely to help consumers elevate their happiness in winning an auction which confirms their smart bidder hypothesis. However, this variation in screening and bidding costs is differentiated among lenders. We formulate two hypotheses regarding the impact of introducing a BA on the attractiveness of the ORA (in terms of the number of bidders and bids in the ORA, Hypothesis H1) and of its duration (Hypothesis H2).

H1a. The introduction of Autolend has a positive impact on the number of bids.

Autolend begins bidding at the ceiling interest rate and then automatically bids by decrements of 0.1 percentage points until the bid is eventually selected or the reservation interest rate is reached. To perform the same task manually is highly time consuming for bidders. Because Autolend automates bid generation and makes the bidding cost vanish, we expect more bids to be generated after introduction of Autolend.

Nevertheless, [14] highlighted that some manual users adopt herding behavior. The use of the BA inhibits this herding behavior and reduces overheated bidding competition which may conversely reduce the number of submitted bids. Yet, the effect associated with automatic bidding is expected to dominate this latter effect, and thus Autolend to have a positive impact on the number of bids. Although we expect an increase in the number of submitted bids, this increase is not necessarily evenly spread among projects. The econometric analysis enables to assess which types of projects are favored in terms of submitted bids, especially with respect to the rating of these projects. Finally, note that in the context studied here, a bidder's investment in a project is limited to €2000. Hence, projects with higher loan targets require more bids, bidders and lenders. For that reason, it is appropriate to measure the number of bids relative to the loan target (the number of bids / loan target).

H1b. The introduction of Autolend has a positive impact on the number of bidders.

Since the use of Autolend decreases the screening and bidding costs, we expect the arrival of new bidders. We also expect that those bidders already operating in the platform are able to invest in more projects. Nevertheless, other effects could counterbalance this trend because of the speed of the BA. First, some users may leave the platform since they are no longer able to correctly observe other bidders' bidding strategies to implement their own. Second, manual bidders may no longer be able to implement a late bidding strategy ([10]) and are thus "crowded out". We here expect the direct impact of Autolend on the number of bidders to be positive because we expect that a large share of lenders will experience decreased screening and bidding costs using the BA. Similarly to H1a, it is more appropriate to measure the number of bidders relative to the loan target.

H2a. The introduction of Autolend reduces target duration.[14]

As a new project is posted online, the campaign starts and all the users who have activated Autolend submit a bid instantaneously if this project matches their selection criteria. Surprisingly, [14] showed that introducing a BA significantly increased the target duration in a P2P lending context. They explained that introducing the BA decreased herding behavior and consequently compelled the users that stick to manual bidding to spend more time analyzing hard and soft information. However, in a P2B context similar to that of our study, [36] argued that lending is a rather passive investment process with

[14] Recall that target duration measures the time elapsed between the date of release of the project on the platform and the date the financial target is met for the first time.

most lenders giving priority to yield and diversification sometimes over a risk assessment that relies on individual expertise. Since we expect that a large share of lenders should experience decreased screening and bidding costs using the BA, we expect that introducing Autolend reduces target duration.

H2b. Introduction of Autolend reduces the post-target duration.[15]

The closing date is a decision made by the borrower who faces a trade-off. Extension of this duration may provide savings on the final interest rate. However, it obviously postpones the date at which funds are available. After Autolend is introduced, all the bidders that use Autolend formulate bids and counter-bids almost instantaneously and so, either the ceiling rate set by the platform or the reservation rate set by the bidder is reached. Since bidders using Autolend cannot modify their reservation rate during the campaign, the borrower cannot expect much saving on interest rates from those bidders. Therefore, after introduction of Autolend, postponing the closing date may enable a saving on interest rates only if manual bidders continue bidding. Since we expect manual bidding to sharply decline after the BA is introduced, savings on interest rates are less likely, which in turn lowers the incentive to postpone the closing date. Therefore, we expect the availability of Autolend to reduce post-target duration.

Assumption B. Autolend impacts the bidding outcome.

The introduction of a BA may not only impact the ORA process but also its outcome. In the more general context of DSSs instantiated as robo-advisors, [44] demonstrate that this type of DSS leads to better investment screening and portfolio optimization. However, [16] demonstrated that a poorly calibrated BA could harm informational efficiency. We here characterize the bidding outcome by two measures, the number of lenders (H3) and the final interest rate (H4). We defined lenders as bidders

[15] Recall that the post-target duration measures the time elapsed between the date the financial target is met for the first time and the date the auction is closed by the borrower.

whose bids are eventually selected (after the campaign has closed) and final interest rate as the post-campaign interest rate (i.e., average interest rate of selected bids weighted by ticket size).

H3. The introduction of Autolend impacts the number of lenders positively.

Prior to introduction of a BA, bidders (and eventually lenders) are constrained to submit bids manually. Since bidding costs are independent of ticket size, they have an incentive to submit bids with high ticket size to save bidding costs. Since portfolio diversification is one of the lenders' investment motives ([36]), we thus expect that lenders using the BA should prefer submitting tickets of lower size and invest in more different projects. Thus, in line with [44], we expect the number of lenders per project relative to the loan target (number of lenders divided by the loan target) to increase with Autolend.

H4. The introduction of Autolend impacts the final interest rate negatively.

Based on H1a and H1a, we expect more bids and bidders after introduction of the BA. Based on this, we should expect competition to be fiercer and the final interest rate to decrease (cf. [26] in a more general context). The specific calibration of the BA may also shape and direct competition. For instance, in the case studied here, the platform provides some advice to lenders as they parametrize Autolend ("advanced mode"). For each loan duration and rating combination, the platform informs the bidder whether the reservation interest rate they have selected is "*competitive compared to usual bids in the same category*" or not. In addition, bidders can prevent the BA from bidding in specific loan duration and rating combinations. Therefore, all else being equal, competition may be increased for some categories and decreased for others. We measure the final interest rate as the average of the interest rate of all selected bids weighted by ticket size since this is the interest rate paid by the borrower if the campaign is successful.

4. Empirical analysis

4.1. Hypothesis testing

Figure 4 shows the per project share of bidders who submitted bids through Autolend and suggests that bidders adopted the bidding agent in a short time span. Table 2 provides descriptive statistics of the variables over the whole sample and distinguishes before and after Autolend introduction. A comparison of the two subsamples leads us to observe an increase in the average number of bids (+536.94), of bidders (+27.98) and of lenders (+6.85). We also observe lower average target duration and post-target duration (by 7.06 and 1.44 days respectively) and lower average interest rate (by 1.53 percentage point).

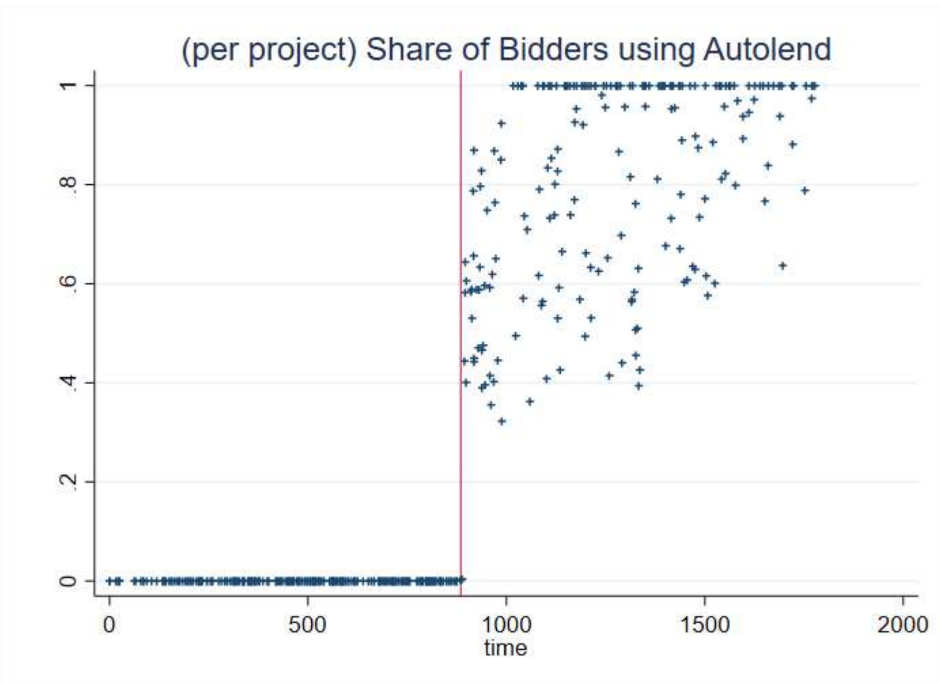

Figure 4. (Per project) share of bidders using Autolend
(the vertical line depicts the time at which Autolend has been introduced)

	Full sample				Sample before BA intro.		Sample after BA intro.	
Variable	Mean	(StD)*	Min	Max	Mean	(StD)	Mean	(StD)
Dependant var.:								
interestRate	7.54	(1.56)	4	9.9	8.25	(1.40)	6.72	(1.33)
nbBidders	25.60	(30.9)	1.61	247.9	12.76	(9.09)	40.74	(39.58)
nbBids	274.1	(516)	2.27	3969	27.69	(23.44)	564.63	(651.6)
nbLenders	9.50	(4.34)	0.89	20.2	6.36	(2.60)	13.21	(2.77)
postTargetDuration	2.88	(3.53)	0	19.05	3.54	(3.29)	2.1	(3.64)
targetDuration	5.27	(7.49)	0	45.22	8.51	(8.20)	1.45	(4.04)
Var. of Interest:								
autolend	0.46	(0.50)	0	1	0	(0.00)	1	(0.00)
rating	0.39	(0.44)	0	1.5	0.39	(0.49)	0.38	(0.38)
loanDuration	40.64	(15.5)	6	60	43.59	(12.74)	37.17	(17.69)
General Control Variables:								
36mTBonds	-0.19	(0.24)	-0.6	0.45	-0.03	(0.21)	-0.39	(0.10)
commerce	0.36	(0.48)	0	1	0.39	(0.49)	0.33	(0.47)
construc	0.05	(0.22)	0	1	0.05	(0.23)	0.05	(0.21)
hotrest	0.09	(0.28)	0	1	0.08	(0.27)	0.09	(0.29)
indagr	0.14	(0.35)	0	1	0.14	(0.35)	0.14	(0.35)
oserv	0.36	(0.48)	0	1	0.33	(0.47)	0.39	(0.49)
grid1	0.25	(0.44)	0	1	0	(0.00)	0.56	(0.50)
grid2	0.12	(0.32)	0	1	0	(0.00)	0.26	(0.44)
loanTarget	78.80	(62.0)	10	400	77.35	(56.00)	80.51	(68.56)
loanTargetlog	4.09	(0.75)	2.30	5.99	4.14	(0.66)	4.05	(0.86)
nbproj	1.10	(1.21)	0	8	1.22	(1.35)	0.96	(1.04)
serial	0.14	(0.34)	0	1	0.08	(0.27)	0.20	(0.40)
time	852.4	(456)	0	1777	495.4	(231.8)	1273.2	(248.8)
turnover	1.91	(4.91)	0.05	83.53	2.08	(6.15)	1.69	(2.42)
Financial Control Variables:								
debt	3.34	(15.2)	-31	206	2.22	(5.14)	4.89	(22.59)
liq	0.20	(0.52)	0	8	0.18	(0.36)	0.24	(0.67)
prof	0.11	(0.13)	-0.2	0.89	0.13	(0.14)	0.08	(0.11)
struct	0.53	(0.19)	0.01	0.91	0.55	(0.19)	0.51	(0.18)
rgDebt	0.19	(0.64)	-1	6.33	0.19	(0.65)	0.20	(0.64)
rgEBIT	4.44	(56.0)	-9.9	1096	6.42	(75.04)	2.00	(7.74)
rgTurn	0.22	(0.59)	-0.7	8.28	0.22	(0.45)	0.21	(0.73)
gDebt	0.55	(0.50)	0	1	0.53	(0.50)	0.57	(0.50)
gEBIT	0.60	(0.49)	0	1	0.63	(0.48)	0.57	(0.50)
gTurn	0.72	(0.45)	0	1	0.72	(0.45)	0.72	(0.45)

Table 2. Descriptive statistics (* StD stands for Standard Deviation)

4.1.1. Methodology

Previous comparisons do not control for variations of other explanatory variables. Therefore, we perform econometric analysis to identify the effect of introducing Autolend on the bidding process and outcome and to test the hypotheses. Our main variable of interest is *autolend*. It captures the introduction of Autolend by a dummy variable that indicates whether Autolend was available to bidders (1, after April 19, 2016) or not (0, before April 19, 2016). In our data, this corresponds to 207 and 244 observations, respectively. We introduce two interaction variables (*autolend* x *rating* and *autolend* x *loanDuration*), as the advanced mode of Autolend requires the bidder to parametrize the bidding agent with respect to these two variables. Doing so enables us to measure the specific impact of those two variables after Autolend is introduced.

We also use a set of general control variables in the main specification. Some control variables are project specific. *LoanTargetLog*[16] and *turnover* control for the amount of the loan target and the company's size, respectively. *Serial* controls for specific impacts for serial borrowers (i.e., borrowers that previously launched a campaign on the platform). To account for potential competition or complementarities among projects available on the platform, we consider *nbproj* (number of projects available for bidding at the time the project is posted online). We also use a set of dummy variables that capture the firm's main sector.

To control for any potential effect of unobserved time-varying variables, we also introduce *time* (number of days elapsed since December 6, 2013 – release of the first project on the platform). As previously noted, we account for the changes in ceiling/floor interest rates by introducing *grid1* and *grid2*. We also control for variations of interest rates in the economy using the rate of return of French 36-month Treasury Bonds (*36mTBonds*). This defines the baseline specification. In the particular case of final interest rate (H4), we add specific control variables that are usually highlighted in the literature as determinants of interest rates. First, we include a nonlinear term (*loanDuration* x *loanDuration*) to

[16] We consider the natural logarithm of the loan target since this variable may exhibit some "overdispersion": a very limited number of projects are characterized by a large loan target which may distort the results.

capture a possible yield curve. Second, we consider three alternative sets of financial variables (see robustness checks in Section 4.2).

The estimation procedure depends on the variable type. We use Ordinary Least Squares (OLS) in the case of the number of bidders (H1a), number of bids (H1b), number of lenders (H3)[17] and interest rate (H4). We use the Cox proportional hazards model to fit duration variables *targetDuration* and *postTargetDuration* in Hypotheses H2a and H2b, respectively.[18] This defines the baseline model from which we test the hypotheses and derive the results. To present and discuss the results, we consider as "statistically significant" only those coefficients for which the p-value is lower than 5%. Robustness checks are detailed in Section 4.2.

4.1.2. Results

Estimations of the coefficients related to Hypotheses 1-3 are reported in Table 3 and those related to Hypothesis 4 in Table 4.[19] Column (1) in Table 3 gives the determinants of the number of bids. The coefficient associated with *autolend* measures the direct effect of the introduction of Autolend. Here, introducing Autolend leads to an average and significant increase of 895.3 bids. Recall that the endogenous variable is defined relative to the loan target (i.e., total number of bids / loan target in thousands of euros) and thus we are able to directly control for the loan target, as a higher loan target requires a higher number of bids and bidders. Hence, the estimation results do not depend on the loan target. Consequently, the direct effect of Autolend on the absolute number of bids should be multiplied (on average) by the loan target.

[17] Recall that since the number of bids, bidders and lenders are measured relative to the loan target, count data models are not relevant (see robustness checks in Section 4.2).
[18] For clarity and without impact on the results, we present coefficients rather than hazard rates in the result table.
[19] Estimations have been performed using the Stata software. Full Stata code is available on request.

	(1)	(2)	(3)	(4)	(5)
	Nb. Bids (H1a)	Nb. Bidders (H1b)	Target duration (H2a)	Post-target duration (H2b)	Nb. Lenders (H3)
autolend	895.3***	23.59***	1.296***	1.367***	1.943***
	(107.7)	(5.654)	(0.364)	(0.352)	(0.491)
rating	126.9**	6.661**	0.0878	-0.0990	-0.305
	(44.97)	(2.360)	(0.146)	(0.155)	(0.205)
autolend x *rating*	-283.4***	-9.095*	-0.621*	-1.571***	-1.690***
	(79.52)	(4.173)	(0.271)	(0.312)	(0.362)
loanDuration	3.661*	0.0899	-0.00815	0.0177**	0.000329
	(1.735)	(0.0910)	(0.00531)	(0.00561)	(0.00790)
autolend x *loanDuration*	-9.099***	-0.363**	-0.00143	-0.0168*	0.00950
	(2.272)	(0.119)	(0.00704)	(0.00752)	(0.0104)
General control variables	Yes	Yes	Yes	Yes	Yes
N	424	424	424	392	424
adj. R^2	0.581	0.651			0.885

Standard errors in parentheses , * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3. Results for testing hypotheses H1, H2 and H3

In addition, we need to consider the indirect effects of Autolend, that is, effects via the interaction variables *loanDuration* and *rating*. The coefficient is negative (-283.4) and statistically significant in the case of the *rating* interaction variable[20] and negative (-9.099) and statistically significant in the case of *loanDuration* interaction variable. With Autolend, the most well-rated projects and those with higher loan durations are relatively less attractive in terms of the number of bids. Those two negative effects might offset the positive direct effect associated with *autolend*. However, everything else being equal, an increase by two digits in the rating scale (switching from the lowest to the highest possible rating) induces 566.8 (283.4 x 2) fewer bids, which is not enough to overcome the direct effect. Similarly, considering the post-Autolend average loan duration (37.17 months), a relatively large increase (+23 months, i.e., 37.17+23 months leading to the maximal loan duration 60 months)

[20] Note that one may also say that introducing Autolend "reversed" in some sense the tendency for bidders to bid on well-rated projects. Pre-Autolend , an increase of 1 digit on the rating scale led to 126.9 additional bids. Post-Autolend, those additional bids were canceled out, because Autolend induced -283.4 fewer bids, which overcame the initial effect.

generates 209.27 (9.099 x 23) fewer bids which does not overcome the 895.3 additional bids associated with the direct effect. Hence Hypothesis H1a is supported.

Column (2) in Table 3 gives the determinants of the number of bidders. Again, we find that the Autolend coefficient is positive and strongly significant: on average, introducing Autolend directly led 23.59 additional bidders to bid on a given project.[21] The coefficient associated with the interaction term *autolend* x *rating* is weakly significant. However, the interaction term *autolend* x *loanDuration* is negative and statistically significant. Hence, after the introduction of Autolend, projects characterized by a higher loan duration received relatively fewer bidders, everything else being equal. This negative effect might theoretically offset the positive one. However, performing similar computations as before[22], the magnitude of this indirect effect is much lower than that of the direct effect. Hence Hypothesis H1b is supported.

Column (3) in Table 3 gives the estimated coefficients related to target duration.[23] The introduction of Autolend had a direct negative impact on the target duration which means that Autolend contributed to reduce the time necessary to reach the financial target. The indirect effects are both non-significant. Therefore, Hypothesis H2a is supported. Column (4) in Table 3 gives the estimated coefficients related to post-target duration. We find that the direct effect of Autolend is to reduce the post-target duration. However, the coefficient of the interaction variable *autolend* x *rating* (-1.571) is significantly less than one. Therefore, the indirect effect may overcome the positive effect. This leads

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[21] As above, recall that this effect is measured relative to the loan target and that the absolute effect of Autolend on the total number of bidders should be multiplied (on average) by the loan target.

[22] Considering the post-Autolend average loan duration (37.17 months), a large increase of, e.g., +23 months (i.e., 37.17+23 leading to the maximal loan duration of 60 months) generates 8.34 fewer bidders, which does not overcome the 23.59 additional bidders associated with the direct effect.

[23] To interpret coefficients, recall that as the coefficient associated with an independent variable is positive, the probability of the event occurring (in this case the loan target is first met) increases and this variable has a *negative* impact on the average duration.

to an ambiguous result: following a conservative approach, we prefer to claim that Hypothesis H2b is not supported.[24]

Column (5) in Table 3 gives the estimated coefficients related to the number of lenders. The direct effect of introducing Autolend is positive (1.943) which means that it had a positive impact on the number of lenders eventually selected by the auction process and thus enhanced portfolio diversification. However, this direct impact is mitigated by the indirect impact via the rating (*autolend* x *rating*). Since this coefficient is negative (-1.690), the overall impact of introducing Autolend depends on the rating of the project. It is negative for the lowest-rated projects (rating = 0), slightly negative for projects rated 1, and positive for the highest-rated projects (rating = 2). Therefore, Hypothesis 3 is only weakly supported, that is, it is supported for low-rated projects but not for high-rated ones. Since the effect is unambiguous for low-rated projects (i.e., high-risk projects), we can argue that Autolend helped portfolio diversification specifically for those projects.

Column (1) in Table 4 gives the determinants of the final interest rate. Interestingly, the direct effect on interest rates of introducing Autolend is not significant: everything else being equal, Autolend did not lead to more or less competitive interest rates per se. The indirect effect associated with loan duration is also not statistically significant. However, the indirect effect associated with the rating is significantly negative. Pre-Autolend, a one-digit increase in the rating scale generated a saving of 0.41 percentage points of the nominal interest rate, on average. Introducing Autolend exacerbated this effect since, post-Autolend, the same increase generated a saving of 0.41+1.339 percentage points, on average. Hence, well-rated projects were favored (i.e., they received lower interest rates) pre-Autolend and our results provide evidence of increased favoring of those projects post-Autolend, since the two effects reinforced each other. Therefore, Hypothesis 4 is weakly supported: it is supported for all projects except those which received the minimum rating. Results are summarized in Table 5.

[24] More precisely, the Cox model uses a nonlinear specification. Hence, the combined effect will ultimately depend on the value of the covariates, e.g., project characteristics, so the hypothesis may be or not supported depending on the covariates.

	(1)		(2)		(3)		(4)		(5)	
	baseline		baseline (no concave yield curve)		baseline + Set 1		baseline + Set 2		baseline + Set 3	
autolend	**0.0300**	**(0.267)**	-0.313	(0.266)	0.00344	(0.276)	0.123	(0.279)	0.0965	(0.279)
rating	**-0.410*****	**(0.108)**	-0.421***	(0.111)	-0.416***	(0.113)	-0.326**	(0.116)	-0.318**	(0.115)
autolend x *rating*	**-1.339*****	**(0.191)**	-1.405***	(0.196)	-1.403***	(0.197)	-1.460***	(0.201)	-1.445***	(0.200)
loanDuration	**0.108*****	**(0.0141)**	0.0404***	(0.00428)	0.106***	(0.0145)	0.105***	(0.0146)	0.105***	(0.0146)
loanDuration^2	**-0.00081*****	**(0.000163)**			-0.000795***	(0.000168)	-0.000806***	(0.000169)	-0.000803***	(0.000169)
autolend x *loanDuration*	**-0.00774**	**(0.00575)**	0.00149	(0.00561)	-0.00663	(0.00605)	-0.00538	(0.00613)	-0.00456	(0.00607)
struct					-0.203	(0.237)				
liq					-0.00490	(0.0811)				
prof					-0.171	(0.342)				
debt					-0.00259	(0.00264)				
rgTurn							-0.0623	(0.0732)		
rgEBIT							0.000690	(0.000732)		
rgDebt							-0.0183	(0.0665)		
gTurn									0.0478	(0.0916)
gEBIT									-0.0875	(0.0843)
gDebt									-0.119	(0.0817)
General control variables:	**Yes**		Yes		Yes		Yes		Yes	
N	**424**		424		411		385		385	
adj. R^2	**0.764**		0.750		0.760		0.765		0.766	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4. Results for testing hypothesis H4 (interest rates)

Hypothesis	Results
H1	Increase in the number of bids and bidders per project
H2	Reduction of the duration of funding campaigns No evidence of a reduction of post-target duration
H3	Lower ticket size on average
H4	No evidence of a global impact on interest rates but a specific positive impact on the well-rated projects (lower cost of capital)

Table 5. Summary of results

4.2. Robustness checks

We performed several types of robustness checks.[25] With respect to all hypotheses (H1-4), we considered an alternative measure of the rating in the form of a less precise rating signal – low (0) if the project received the lowest rating (3 in the original rating scale) or high (1) if the project received a higher rating. This might be relevant if lenders are more severe as they discriminate between projects based on rating. We also introduced loanTarget in absolute terms (instead of using a log scale). We also combined these two changes. Our results are preserved in all these specifications.

With respect to Hypothesis 1a, 1b and 3, we also considered the absolute number of bids, bidders and lenders, respectively, instead of the number relative to the loan target. We used Poisson and negative binomial estimation models because of the nature of the dependent variable. The results are less stable in those specifications but, as expected, the loan target becomes a key determinant which is detrimental to the significance of all other factors. However, as already pointed out, there is a direct link between loan size and the number of bids/bidders/lenders because bidders are constrained to invest no more than €2000 in a given project and the total amount bidders may invest is limited by the size of their portfolios. Therefore, those specifications may only reflect the presence of these two constraints.

[25] Available in the supplementary material associated with this article.

With respect to Hypothesis 4, we contrasted three types of information structure related to the financial variables. First, using the data available on the platform, we computed four complementary financial ratios: liquidity, debt, and profitability ratios (Set 1). Computation of these ratios requires the bidder to have a high financial literacy. These financial indicators are typically used in financial corporate analysis, so this specification might be valid if the crowd has expert financial skills.[26] Then, we considered a second set (Set 2) that includes the year-to-year growth rate of relatively simple financial aggregates (EBIT, turnover, liabilities, debts). Computation of these requires less financial literacy compared with Set 1.

Finally, we considered the same set of variables as in Set 2 as a binary variable (1 if increase over the last year, 0 if not), so Set 3 requires even less financial literacy. This enables us to contrast alternative sets of information depending on bidders' financial literacy. Results are reported in Columns 3-5 of Table 4. In none of these specifications are the coefficients associated with financial variables significant. This suggests that the interest rates set by the crowd of lenders are essentially driven by the platform rating. We finally ran an omission test (omitting the Unilend rating, which may itself depend on some financial variables and ratios). Results with respect to H4 are preserved and financial variables are still non-significant.

Before/after analyses can be sensitive to changes in unobserved variables that may be associated with the timing of the event. Therefore, in addition to the checks described above, we need to consider possible unobserved variables. Autolend was introduced in 2016 and there may differences in the "early" and "late" markets in this study (i.e., before and after 2016). First, it should be stressed that visual inspection of the time series of the endogenous variables suggests a clear-cut change in the short run following the introduction of Autolend. To the best of our

[26] See also [Anonymous] for a specific analysis of this issue. That study uses a subset of the dataset used here since most data were not available at the time of that study.

knowledge, there were no other events in the same time period to explain such a change. However, we can expect differences in the early vs late market to have more diffused effects. We introduced a time variable in order to capture some of those changes, especially learning effects on the platform. We also control for the level of interest rates in the economy which can influence the attractiveness of the platform. However, this cannot eliminate other possible factors. Based on our knowledge of the French crowdlending market, we identified two such factors.

Platform competition may be a source of concern (and more indirectly competition from banks). The Unilend platform was a first mover in this market but faced the entry of several other platforms over the period of the study, which led to intense competition. This may naturally influence the number of bidders and SMEs in the platform. In particular, we could expect competition from other platforms to result in fewer bidders and lenders and longer campaign durations (all else being equal). Unfortunately, there is no statistical measure of platform competition (and even of bank competition) over the whole period. However, our results suggest that introducing the BA had the opposite effects, namely, more bidders and shorter campaign durations. Thus, we shall expect that, had competition been less fierce, the observed impact of the BA would have been enhanced. Hence, we expect that introducing an indicator of competition in our econometric analysis would reinforce our results.

The second factor relates to the size of the crowdlending market, which experienced continuous growth over the period 2013-18. Unlike the previous argument regarding competition, this growth may have contributed part of the effects attributed to Autolend. Unfortunately, there is no time series available over the whole period to directly control for both variables. However, recall that the *nbproj* variable (number of projects available on the platform three days prior to the campaign) is included as a control variable in the regressor list. The number of projects is directly related to competition (the higher the competition the fewer projects available) and to market size (the higher market size, the more projects available). Therefore, *nbproj* can be considered as a valuable proxy of the two factors mentioned above.

5. Discussion

Our results enable a precise assessment of how introducing the Autolend BA, in the context of a P2B lending platform, influenced coordination between the two sides of the platform and the efficiency of the transaction process. We provide evidence that introducing a BA attracted more bidders to the auction process. We also show that introducing the BA led to a dramatic increase in the number of bids per project and enhanced competition. In addition, we provide evidence that the BA dramatically reduced the duration of funding campaigns. Such a reduction benefits both lenders and borrowers. In terms of interest rates, our analysis led to subtle results. We find that introducing the BA had no direct impact per se. However, we identify an indirect impact associated with the platform's rating, as introducing the BA benefited well-rated projects more than low-rated ones. Well-rated projects received lower interest rates prior to the introduction of the BA and the BA reinforced this pattern.

As a corollary of our results, we also provide evidence that introducing the BA induced an increase in the number of selected lenders, but only for less well-rated projects. This result suggests that, thanks to lower transaction costs, introducing the BA enhanced portfolio diversification for lower-rated projects. Finally, we did not find clear evidence that introducing the BA resulted in a shorter post-target campaign duration, because the final impact may depend on the value of other covariates. These results contribute to the literature on ORA processes by empirically documenting how the interplay between two DSSs (a BA agent and a rating-based DSS) impact on auction processes and outcomes.

5.1. Managerial contribution

Our results suggest new insights about the role of IS, specifically a BA, for two-sided platforms [5]. Platform owners need to find the best mechanisms to attract lenders and borrowers on both sides of the trade. On one side, platforms need to attract enough viable projects to enable lenders' portfolio diversification. At the same time, they must select the projects characterized by the most sustainable creditworthiness to minimize default risk. On the other side, SMEs need to make sure that their project will attract a large number of potential lenders in order to be rapidly funded [31] and to benefit from a low interest rate. The design of two-sided platforms defines a precise set of trading rules and interactions and its crucial role is emphasized by [2] (see also [7] and [5]).

We show that in the case of P2B crowdlending, platforms can also choose to invest in the non-lucrative side (here lenders) where there are positive screening and bidding costs. As described above, the BA is provided only to lenders but it ultimately affects the experience of both sides. If the crowd is made of lenders characterized by low levels of financial expertise ([36]) then the BA enables savings of screening and bidding costs for bidders, which enables the platform to enroll more bidders. This generates cross-side network externalities that benefit the other side. In turn, borrowers should be attracted by shorter campaigns and interest rate savings, especially for well-rated projects. Our results show that, all else being equal, lower-rated projects benefitted from shorter durations after the BA was introduced. Higher-rated projects benefited from shorter duration but also from additional savings on interest rates. The BA thus has positive impacts on all types of borrowers but also particularly favors high-quality projects. Attracting this type of project is crucial for P2B lending platforms in order to minimize their annual default risk and improve their reputation in the long run. Also, lenders need high-quality projects but also lower-quality projects because competition on interest rates is fierce on high quality projects. The coexistence of projects associated with different levels of risk and interest rates helps to minimize portfolio risk and to attract more and more lenders.

More generally, our work highlights that IS-based investments can be used as an alternative to monetary instruments to attract lenders and borrowers. Crowdlending platforms typically charge fees comprising a commission, based on loan size, plus a fee based on a percentage of the outstanding capital incorporated into the monthly repayments. Platforms compete to enroll more borrowers and lenders. To achieve this, they can offer price cuts. However, doing so has a direct negative effect on their revenue in the short and medium terms. Our results suggest that an IS-based investment in the form of a BA can be effective both to enhance the convergence of interests of the two sides and to increase platform revenue.

5.2. Regulatory implications

According to [13], the "*inappropriate use of ORA is a source of conflict and threatens trust relationships*". If a high rate of fundraising success is linked with a high default rate and with bankruptcy issues, it may expose lenders in the crowd to excessive and misperceived risk. To mitigate this issue, lenders should be assisted in their decisions by rating-based DSSs whose design is connected with accurate predictors of default rates. Interest rates should ultimately reflect the economic fundamentals and risk profile of each project, in order to avoid adverse selection. Even if this research does not focus on the rating per se, it sheds light on its particular importance in lenders' decisions and outcomes, since introducing the BA reinforced the impact of the rating on interest rates. In the case of Autolend, this BA restricts the number of parameters that define the formulation of an investment decision to two (the project's rating computed by the platform and loan duration) instead of a richer set of information (soft and hard information).

[30] developed this argument in the context of equity crowdfunding. Our study extends this argument to the context of P2P crowdlending and has to be discussed together with lenders' degree of financial literacy. Expert lenders will be frustrated by such a reduction in the information set while non-expert lenders will find it convenient. Hence, on the one hand, expert lenders may have to exclude some information while, on the other hand, non-expert lenders may rely excessively on the rating.

The dependency of bidders on the rating may be problematic if it is based only on trust and bidders do not exactly know or understand how the rating algorithm is computed. This raises an issue about the internal algorithm used to compute the rating. As lender trust in the rating is high and lenders rely heavily on the BA, which in turn relies heavily on the rating-based DSS, the regulatory framework should be more precise about the transparency of the rating process. Specifically, if the in-house, rating-based DSS is totally connected with the BA, more information should be given to lenders and borrowers about the algorithm used to determine the rating. Another recommendation is to use an external rating, such as those provided by ECAI[27], to complement the in-house rating. A final recommendation is to involve an impartial third party, such as a certified public accountant, to guarantee the accuracy of corporate accounts and the suitability of the in-house rating process.

6. Conclusion

We considered a P2B lending platform which introduced Autolend, a BA in the context of an ORA. This BA enables lenders to automate both the formulation and the implementation of their investment strategy. We contrasted funding campaigns before and after the BA was introduced to investigate its impact on the auction processes and outcomes. We find that the BA had a positive impact on the number of bids and bidders in the auction and reduced the time necessary to collect funds. It also positively impacted the number of lenders and enhanced portfolio diversification. With respect to interest rates, we found that the BA had no direct impact but had an indirect one: after the BA was introduced, well-rated projects benefited from extra savings on interest rates, everything else being equal. These results show that introducing a BA improved the overall efficiency of the ORA but that it was not neutral towards borrowers and may, combined with a rating-based DSS, increase discrimination among projects. It also sheds light on the potential consequences of a disconnection between perceived and actual risk levels.

[27] *External Credit Assessment Institutions*. See Art. 120, 121 and 138 of EU Regulation No. 575/2013 (CRR). See also https://eba. europa.eu/regulation-and-policy/external-credit-assessment-institutions-ecai.

This research can be extended in two directions. In this paper, we used project-level data and focused on the crowd's decisions and on aggregate outcomes. It would also be fruitful to consider more granular data documenting user behaviors. For instance, this research provides an indirect measure of portfolio diversification and it would be interesting to use a lender-based dataset to analyze the impact of the BA on risk exposure conditional on lenders' financial literacy. Second, unlike research on reward- or donation-based crowdfunding (e.g., [34]), we did not investigate the success of funding campaigns in this study. As has been mentioned, this is because failure is a marginal phenomenon in the platform studied here, as in most platforms operating during the same period. However, the high success rate may be due to the macroeconomic environment during the period we studied and it would be interesting to consider alternative environments and analyze whether the combined use of DSSs (BA and the rating-based DSS) may orient the crowd's funding decision to some specific types of projects on those platforms.

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