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Platform Perils: The winner's curse on B2C consumer lending platforms

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Abstract

This article compares the estimate of credit risk and actual defaults on unsecured loans originating from a B2C lending platform to a bank with those taken directly from the same bank. Our study expands on earlier research by comparing credit scoring and default-level differences through simulations of banks' bidding process for a loan with similar credit risk models. Banks systematically and significantly underestimate the risk of loan applications through the B2C lending platform. The bank also experiences a disproportional loss of profitable clients on platform loans. Credit risk models from direct lending should be adjusted for this bias before they are employed in platform lending. Both effects can be linked to a winner's curse consistent with both theory and simulations, which is not previously explored.

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1 Introduction

This study explores the vulnerability of how a credit model estimates risk by comparing credit risk estimates on unsecured loans in marketplace lending portals and direct lending from the bank. Furthermore, this study analyzes differences in loan default levels and the proportion of clients switching to other banks after the loan was granted.

Marketplace lending (MPL) is a rapidly growing alternative to traditional lending and distribution channels (Deltas & Engelbrecht-Wiggans, 2005; Klafft, 2008; Morse, 2015; Einav *et al*., 2016; Milne & Parboteeah, 2016). Borrowers enjoy reduced search costs and more bank offers. However, a bank's credit model can perform differently when many banks are bidding simultaneously for the same client. To our knowledge, no previous empirical studies have compared B2C marketplace lending to direct bank lending.

Ex-ante bidding on loans can be similar to "the winner's curse" in common value auctions (Kagel & Levin, 1986, 1993). Our unique micro-data gives access to both the ex-ante estimate and enables the calculation of the ex-post value of the loan after repayment or default. Thaler (1988) categorizes the winner's curse as an anomaly. However, this study investigates whether the winner's curse occurs when a bank bidding for a loan fails to adjust its bids for the number of bidders and the uncertainty levels in a credit risk model. We then compare the actual outcomes from our micro-data to the expected result from simulations of naïve bidding process with multiple similar banks.

Our research is the first to explore the pitfalls a bank face in B2C marketplace lending by 1) providing an example of a false signal from credit scoring, which makes marketplace lending seem less risky; 2) exploring if a significant winners curse exists in B2C marketplace lending, 3) determining if significant differences in customer retention of less risky clients increase the effect of a winners curse, and 4) illustrate how empirical data are consistent with naïve bidding.

2 Materials and Methods

2.1 Data

Our data consist of loans from three major B2C marketplaces in Norway, and a dataset of comparable loans originated through marketing by the same bank. The data include estimates of all clients' credit scores from one generic and one proprietary credit model[1] and the observed default level on all loans 16 months after the loans are granted. Table A-I in the Appendix presents the descriptive statistics, and Table I shows the differences between loans granted on the bank's three platforms.

We investigate borrowers who choose offers from a bank from two different sources: direct applicants (N–23,270) using the bank's online application form, which results in clients borrowing from the bank (N–1,439), and applicants using one of the three different lending platforms in which the bank competes with up to 20 other banks (N–75,710) and grants a total of 2,807 loans through B2C platforms between 2017 through 2020. The bank competes with all applicants and grants loans with acceptable credit risk. Clients are limited to the granted loans that the applicants choose to take. The lending platforms display all offers to the client, ranging from the lowest to the highest effective interest rate.

To illustrate whether our empirical results coincide with theoretical results, we prepared a dataset for our simulation with customer characteristics representative of the data supplied by the lending marketplace to the participating banks. Our simulation illustrates the effect of similar banks competing with similar credit models in naïve bidding for the same clients. We assume that loan applicants choose the lowest price and that banks employ risk-based pricing models.

2.1 Modeling price and profitability

The price offered to clients for unsecured loans highly depends on credit risk (Edelberg, 2006). Based on a credit model, the banks set a non-negative price on loans with a uniform size and payment plan. If a rational client is offered a loan with a price lower than that client's willingness to pay, the rational client chooses the lowest price from the banks offering a loan.

$$\min_{Price<Price\ max}[a, b, c.\dots.n] \tag{1}$$

With an increase in the price offered by a bank, the bank reduces the probability of being chosen by the client. With risk-based pricing, the likelihood of a bank winning increases when the bank has a lower estimate of credit risk than the credit risk estimated by the other banks. When credit score models have some level of uncertainty, this intuitively leads to the probability of winning increasing when a bank's credit score model underestimates the actual risk (i.e., a winner's curse). The number of bidders increases the probability of the winner's curse (Peeters & Tenev, 2018). We explore whether the increase in the winner's curse is evident when comparing

[1] Details on the credit models available on request to authors.

unsecured loans through a B2C lending platform with direct applications to the bank. On B2C lending platforms, the applicant simultaneously receives offers from many banks. However, direct applicants to the bank will generally have a significantly lower number of offers, thus allowing us to explore Peeters and Tenev's (2018) findings empirically. Further, we explore how the informational asymmetry from differences between a generic credit score and the credit score of the inside bank can influence the probability of clients switching, as proposed by Reite (2022) in a study of mortgage clients, and expand this study to credit score differences in B2C marketplace consumer lending.

We propose that the profitability of a loan with a uniform size and payment plan through a distribution channel with risk-based pricing is dependent on the following:

$$P = \alpha + \beta C + \gamma R + \delta L + \varepsilon \tag{2}$$

Where:

P = recorded profit on a loan (net income after funding cost, loss, and loss provisions).
C = error in the measure of credit risk since an underestimation of risk leads to a lower price relative to the correct risk-based price. Overestimation of a client leads to a higher price relative to the correct risk-based price, thus improving profitability operationalized by comparing a client's credit score in a bank's internal risk model and comparing this score with the score in a generic credit scoring model.
R = retention of loan client since client retention is the basis of receiving interest rate payments on loans.
L = losses incurred on loan during the time studied.
ε= error term.

We test this model empirically with our loan and application data and compare results with the results from a simulation with naïve bidding for a client on a lending platform.

3 Results

Figure 1 summarizes applicants' and clients' credit scores from our micro-data. We observe that loans granted to clients, on average, have higher (better) internal credit scores than the applicants. More interesting is that we also observe a higher internal credit score of loan clients acquired from the lending platform than those acquired directly from the bank's online application form.

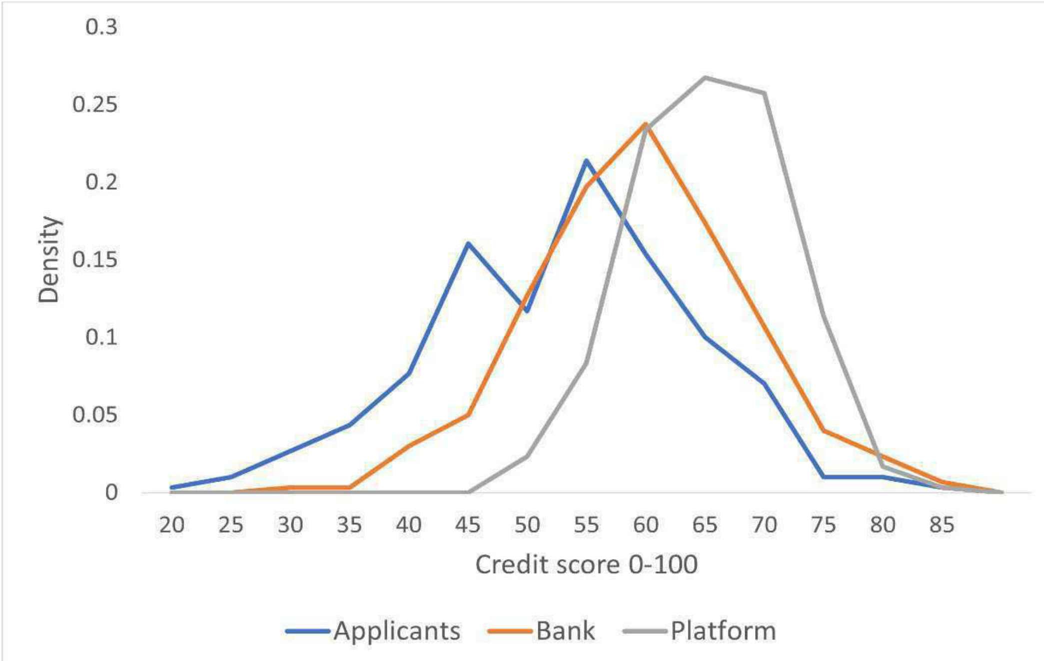

Figure 1: Credit scores of all applicants and clients granted a loan in the bank through a platform compared to those borrowing directly from a bank

Comparing these observations with a simulation of a naïve bank granting loans to the applicant base and a simulation of several naïve banks competing with similar credit models on a platform in Figure 2, we observe a striking similarity between the simulated and actual results. The higher credit score of clients granted loans through a platform seems consistent with the bank accumulating clients where the bank’s credit model underestimates the actual credit risk.

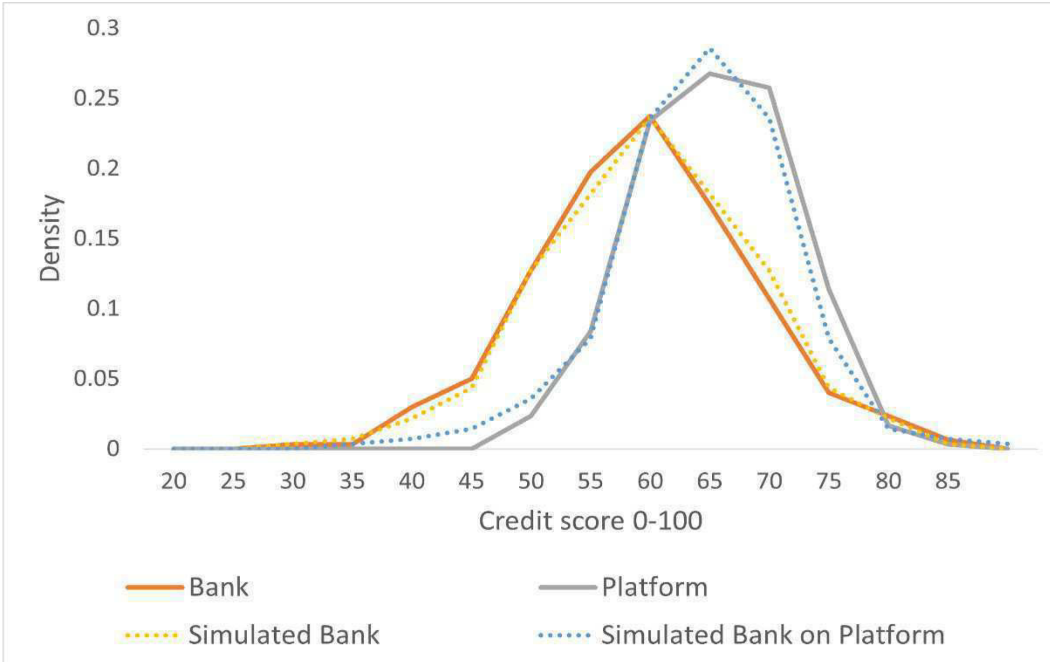

Figure 2: Credit scores of clients granted a loan in the bank through a platform and those borrowing directly from a bank compared to credit scores with simulation and banks operating in naïve competition on a platform with other banks employing the same credit model

Thus, the initial credit score difference between direct applicants and loans from an MPL platform can constitute a false positive signal (illustrated in Table I panel a below).

Table I: Differences in credit score, default levels, and churn between loans directly from the bank and from three different B2C marketplace lending platforms

a) Credit score difference	**Bank – Generic[1]**	**N**	**s.d**	**p-value of difference**	
Bank	-10.853	1,439	68.373	-	
Platform 1	-2.337	938	70.484	0.004	**
Platform 2	11.627	629	70.041	<.001	***
Platform 3	7.523	1,240	70.402	<.001	***

b) Default levels	**Default**	**N**	**s.d**	**p-value of difference**	
Bank	0.205	1,439	0.404	-	
Platform 1	0.235	938	0.424	0.091	.
Platform 2	0.245	629	0.414	0.004	**
Platform 3	0.259	1,240	0.438	0.001	**

c) Churn if Credit Score Bank<Generic Score	**Churn[2]**	**% Loans**	**s.d**	**p-value of difference**	
Bank	0.271	60 %	0.466	-	
Platform 1	0.314	52 %	0.394	0.065	.
Platform 2	0.378	42 %	0.423	<.001	***
Platform 3	0.433	44 %	0.471	<.001	***

1) "Credit score difference" is the difference between the credit score calculated by the bank's internal credit risk model and the generic credit score from a credit rating agency (Credit score internal – Credit score bank). A negative value signifies that the banks' estimate of credit risk is lower than in the generic credit score, thus indicating a higher estimated risk.
2) "Churn" is defined as loans refinanced by other credit institutions/banks in the first 24 months since the origination of a loan.
3) Significance levels 10% "." ; 5% "*"; 1% "**"; 0.1% "***"

Table I further shows that while the internal credit score of clients through a platform seems higher, this does not reflect a lower risk but a higher default level (illustrated in Table I, panel b) of losses than direct applicants to the bank. This strengthens the hypothesis that the credit score difference between loans through MPL and directly to the bank is a false positive signal from a winner's curse.

We also show in Table I (panel c) that the bank loses more of the clients where it has overestimated the risk and that on loans originated from platforms, there is a significantly higher loss of clients than in cases where the bank has overestimated the risk, and thus offered a less advantageous price. While only significant at a ten percent level for loans through platform 1, the effect for the two other platforms where the bias in the bank's internal credit score compared to the generic credit score difference also is higher (Table I, panel a). Platform 1 differs from the other platforms by only comparing offers from up to four banks as opposed to 12-20 banks competing for a loan on platforms 2 and 3. This further substantiates the link between the size of a winner curse and the number of banks competing on a platform.

Table II: Factors influencing the profitability of a loan

	Model 1	Model 2	Model 3	Model 4
(Intercept)	-0.011 (0.006)	-0.007 (0.007)	-0.008 (0.007)	-0.008 (0.007)
Credit score difference – C	-0.211*** (0.014)	-0.266*** (0.015)	-0.208*** (0.017)	-0.211*** (0.014)
Retention of client – R	0.071*** (0.013)	0.071*** (0.013)	0.071*** (0.013)	0.071*** (0.013)
Loss in the period – L	-0.115*** (0.016)	-0.113*** (0.016)	-0.104*** (0.014)	-0.107*** (0.013)
Control variables:				
Age, sex, geography		✓	✓	✓
Income, net wealth, homeownership		✓	✓	✓
Platforms a, b and c				✓
Platform interactions				
Platform: Credit risk difference - C			-0.078*** (0.021)	-0.103*** (0.028)
Platform: Retention – R			-0.014** (0.005)	-0.027* (0.011)
Platform: Loss in the period – L			-0.057*** (0.007)	-0.048*** (0.009)
Adjusted R^2	0.221	0.232	0.274	0.302
VIF max/average	1.102/1.030	1.079/1.040	1.152/1.045	1.219/1.055
N	4,246	4,246	4,246	4,246

1) Standardized regression, robust standard errors. Dependent variable Profitability of a loan (P) from Equation 2
2) Significance levels 10% "." ; 5% "*"; 1% "**"; 0.1% "***"

Turning to Table II, we observe that a higher credit score in the bank relative to the generic credit score leads to significantly lower profitability [-0.211, (0.014)]. Non-surprisingly higher retention increases profitability [0.071, (0.013)], and losses incurred during the observation period reduce profitability [0.115,(0.016)]. These factors remain significant when controlling for income, net wealth, homeownership, and whether a client originates from the bank or through platforms. More interestingly, we find a significant interaction between credit risk, retention, and the effect of losses when introducing control for platforms in Model 3 and further when controlling for differences in the three different platforms in Model 4. These findings are consistent with the differences observed in Table I. Platform clients display larger differences between the credit risk estimates, lower retention, and higher losses.

Thus, the bank systematically underestimates the risk from loans originated through a B2C lending platform and loses significantly more clients where the bank has a higher risk estimate than the generic model. This disproportionate loss of clients where the bank overestimates risk leads to a reduction in the profitability of loans through platforms, as more high-risk clients stay from both B2C lending platforms and the bank.

4 Conclusion

When comparing acquisition costs and risk through an MPL platform with direct lending, a bank should consider the underestimation of risk, the higher default levels, the lower retention of clients, and the bias towards losing clients with lower risk in marketplace lending found in this study. We suggest that bias in the risk estimate can be identified by comparing the banks' credit risk model and generic models. To consider this bias, the banks' credit risk models from direct lending should be adjusted before they are employed on lending platforms. Adjusting the price offered in marketplace lending upwards to reduce the risk of attracting unprofitable clients can lead to an increase in the proportion of low-risk clients quickly leaving the bank, thus leaving the bank with a disproportionate number of clients with underestimated risk and a high probability of default. Our findings are of importance to banks offering loans through lending platforms, as well as to platform providers in implementing measures to reduce the risk of false positive signals from credit scoring and consequences of the winners curse in platform lending, as well as to regulators who may want to curb the increase in the supply of credit to high-risk clients that can result from the winner's curse in platform lending. The study is limited to micro-data from one bank. The loss levels of the bank in the study are lower than the average loan loss provisions reported by other Norwegian banks in the period studied (Norwegian Financial Supervisory Authority, 2021). Expanding the analysis to more banks would improve the generalizability of our findings.

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Appendix

Table A-I: Descriptive statistics of clients borrowing through a platform and those borrowing directly through a bank

	Variable	N	Mean	SD	SE
Bank	Net assets	22,854	66,765.3	719,677	4,760
	Years employed	23,209	3.158	2.513	0.0165
	Net income	22,854	304,395	394,456	2,609
	Credit score generic	23,270	444.169	148.207	0.9716
	Credit score bank	23,270	51.039[1]	17.455	0.114
Platform	Net assets	75,319	70,018	758,918	2,765
	Years employed	75,680	5.128	6.69	0.0231
	Net income	75,319	327,586	254,043	925.670
	Credit score generic	75,710	485.313	99.825	0.363
	Credit score bank	75,710	54.546[1]	17.056	0.062

(a) Applicants to the bank based on source

	Variable	N	Mean	SD	SE
Bank	Net assets	1,437	154,488	711,632	18,772
	Years employed	1,416	4.01	2.25	0.06
	Net income	1,437	438,837	340,124	8,972
	Credit score generic	1,440	566.42	85.15	2.24
	Credit score bank	1,440	68.93[2]	9.64	0.25
	Default 18 M	1,440	0.205[3]	0.404	0.0104
Platform	Net assets	2,738	354,821	124,9073	35,499
	Years employed	2,724	7.12	8.56	0.24
	Net income	2,807	423,432	275,749	7,837
	Credit score generic	2,806	588.40	90.26	2.56
	Credit score bank	2,807	73.88[2]	9.37	0.27
	Default	2,803	0.249[3]	0.3801	0.0108

(b) Clients based on the loan source

1) The credit score of clients who accept an offer from a platform is significantly higher than that of those who accept an offer from a bank at a 1% confidence level.

2) "Default" is defined as a scenario where one payment is overdue by more than 45 days at the time of measurement and within the first 18 months after issuing the loan.