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DETERMINANTS OF DEFAULT IN P2P LENDING: THE MEXICAN CASE

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ABSTRACT

P2P lending is a method of informal finance that uses the internet to connect borrowers with on-line communities. Through limited participation of financial intermediaries, P2P credit becomes a new model for unsecured loan origination. The question framing this research is: What are the elements that could help on-line financiers characterize default risk in these loans? It attempts to advance knowledge about P2P default determinants, from the perspective of the availability of information to on-line lending communities in emerging countries. With the aid of a logistic regression model and data provided by Mexican platforms and public information available to on-line investors, this inquiry explores the effect of credit scores and other variables related to loan and borrower´s characteristics over P2P default behavior. The results showed that information provided by the platform is relevant for analyzing credit risk, yet not conclusive. In congruence with the literature, on a scale going from the safest to the riskiest, loan quality is positively associated with default behavior. Other determinants for increasing the odds of default are the payment-to-income ratio and having been refinanced on the same platform. On the contrary loan purpose and being a female applicant reduce such odds. Evidence from the sample showed that under equal credit conditions, a case for differential default behavior among variations in gender, age or geographical location, could not be established. However it was found that having controlled for loan quality, women have longer loan survival times than men. This is one of the first studies about debt crowdfunding in Latin America and Mexico. Implications for lenders, researchers and policy-makers are also discussed.

Keywords: Peer-to-peer lending, default risk, emerging countries, Mexico, loan survival, logistic regression, differential default behavior

1. INTRODUCTION

New means of project sourcing have flourished with the advent of the Web 2.0 and the upcoming popularity of online communities (ITURBIDE; CANFIELD, 2015). On-line financing and the development of crowdfunding platforms (CF) that evolved from the Fintech ecosystem constitute an example of a disruptive business model innovation (MARKIDES, 2006).

With limited participation of financial intermediaries, online peer-to-peer (P2P) or market-place lending becomes a new model for unsecured loan origination (GALLOWAY, 2009), where anonymous backers parcel the amount loaned. Allegedly P2P lending constitutes a good alternative for the financing community. Borrowers receive better credit conditions than in traditional finance; Creditors take advantage of an investment model where risk is coupled to the credit rating of the funded loans (BACHMANN, et al., 2011) and lending websites benefit by raising fees for successfully realized transactions.

P2P lending initiated in the U.K with the first online lending platform, Zopa (HULME; WRIGHT, 2006) and is also developing apace around the world (WAN et al. 2016; WEISS et al. 2010; BERGER; GLEISNER, 2009). Various P2P platforms have evolved from the Mexican Fintech ecosystem; some of them operate nation-wide. The loan approval rate for these platforms is less than 5%, a common figure for this type of financial product (HAND; HENLEY, 1997).

The purpose of this article is to attain further understanding about applicants´ delinquent credit behavior in P2P lending activities, in emerging markets, particularly in the Mexican context.

This study will address the following question: 1) what are the elements that could help on-line financiers characterize default risk in these loans?

Platforms collect information about the applicants and feed their credit rating algorithm. As it´s the case of many on-line lending sites, each loan is classified according to its risk characteristics, assigning a corresponding loan rate believed to capture credit risk. Grades and loan rates increase with the evaluated risk. In our

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sample, over a reverse scale, loan quality is measured ranging from A down to G, with three notches each; Where Grade A defines the highest quality loans charging 8.9% p.a., and Grade G, which contains the riskier credits, charges 28.9% p.a. in the lowest notch.

Arguably, some of the most important sources of concern for lenders in credit markets derive from information asymmetry (IA), which stems from the fact, that borrowers are better informed than lenders on at least two conditions that basically shape credit and re-investment risks: (i) the ability and willingness to repay the debt and (ii) the propensity for early payment. in this research, only credit risk arising from default behavior is analyzed.

Creditors benefit from knowing the true characteristics of borrowers, but moral hazard hampers direct information sharing (IS) between market participants. IS and monitoring activities lie at the base of financial intermediation where a stream in financial theory considers that through IS, financial intermediaries can reduce the adverse consequences of private information problems and transaction costs.

For that matter, the following argument constitutes the base for the present study: In P2P lending, the platforms collect valuable information for understanding default behavior, sharing it with the lending community in an attempt to mitigate the adverse effects of IA, moral hazard and adverse selection.

Investors rely on the quality of the rating process, but “soft and self-reported” information also play important roles in the screening process (RUIZ-UGARTE, 2010). Authors such as Khwaja et al. (2009) found that lenders infer the most from standard banking “hard” information but likewise they use non-standard information, particularly when it provides credible signals regarding borrower´s creditworthiness. Some lenders even go further as to check looks and race as observed proxies for the determinants of default (DUARTE et al. 2012; RAVINA, 2012).

Statistical discrimination around appearance and popularity has not always proved effective in understanding delinquent behavior (FREEDMAN; JIN, 2014; RAVINA, 2012, POPE; SYDNOR, 2011). In all cases, evidence provides sound warning that return-maximizing investors should be careful in interpreting social ties, appearance and other social characteristics alone, when screening for loan applicants.

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Through the platform´ s web-page, backers have access to credit grades, direct messaging with borrowers, and allegedly to relevant information about the applicant´s characteristics and loan conditions that will help them identify default risk. This is an important step further to allow on-line lenders to overcome private information problems. In that sense this inquiry attempts to study, from the lender´s perspective, the pertinence of the information provided to the backers by the web-site.

In many ways, the present research looks to contribute to the comprehension of this new and fast-paced P2P ecosystem. For one thing, notwithstanding the existence of extant literature about credit rating and its effect over on-line lending behavior (Cf. BACHMANN, et al., 2011 for a survey), academic work in the field tends to concentrate geographically in developed countries like the United States, Germany and other European countries, or in China as well, where P2P lending activities have flourished in the recent past (WAN et al., 2016).

Most studies use rich data sets from P2P platforms such as Prosper, Lending Club and Smava, and in that sense, to the best of our knowledge this study is one of the few that analyzes lending behavior in on-line communities in emerging countries, particularly in Latin America where this activity is relatively new. From the lenders, academics and policy maker’s perspective, this research is important because it´s one of the first that considers the Mexican crowdfunding and P2P ecosystems, currently under construction.

This investigation identifies relevant variables based on collected demographic and financial characteristics and, using a multivariate regression analysis framework, estimates default probabilities and analyzes the effect of gender on delinquent behavior, after controlling by loan quality. Finally and based on gender and age, this study examines the loan survival times of borrowers in order to provide a better view of the possibility of differential non-payer behavior in the Mexican P2P environment.

To preview our results the model shows that information provided by the platforms and available to financiers is relevant for analyzing credit risk, yet not conclusive. The most important determinants for increasing the odds of delinquent

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behavior, besides the credit score are those related to the ratio of monthly payment to income and having been refinanced on the same platform.

On the other hand, loan purpose and being female reduce such odds. Characterized by credit rating, being a female applicant is relevant in positively determining loan default only in credit scores C and F, consequently there is no conclusive evidence that, under equal credit characteristics, lenders might benefit by screening default behavior by gender in this sample. However it was found that women have longer loan survival times measured in months (9.2) than men (5.4).

Overall, at equal credit ratings, women have better default behavior, as measured by loan survival times alone. The above mentioned results are in line with those found in the incipient literature of P2P lending and contribute to three streams of knowledge; Being, the effects of case and statistical discrimination in financial services, the study of determinants of default and differential attitudes toward delinquency by gender and age, and research in the recent field of P2P lending.

The remainder of the article is organized as follows. Section II provides an overview of the existing literature. The generality of lending processes at P2P platforms and data collected are described in Section III. Section IV provides the research hypothesis and the test methodology. Section V reports the estimation results of the logistic model and the survival tables and Section VI concludes.

2. LITERATURE REVIEW

P2P lending is a new method of informal finance initiated in the U.K and which is also developing apace around the world. This model for loan origination uses the internet to directly connect borrowers with on-line communities. Various authors have studied the up-surge and evolution of market-place lending (BERGER; GLEISNER, 2009; BACHMANN et al., 2011).

With limited participation of financial intermediaries, these types of platforms facilitate unsecured micro-credits. Arguably P2P lending gives lenders the opportunity to increase their income and offers debtors a means of accessing financing which could not have been possible when there are strong requirement for approval by the traditional financial intermediaries (Zeng, 2013).

Conceptually, financial intermediation (FI) theory sets the foundation for market-place lending based on transaction costs (SCHOLES et al. 1976). It has

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been argued that FI could be used for alleviating the effects of market failures such as adverse selection and moral hazard (PAULY, 1974; AKERLOF, 1970; ALLEN; SANTOMERO, 1997).

Hence, information asymmetry (IA) is perhaps, one of the most important sources of concern in finance markets, leading to credit rationing (STIGLITZ; WEISS, 1981). IA stems from the fact that borrowers are better informed than lenders about their ability and willingness to repay the debt (credit risk) and the propensity for early payment (re-investment risk).

Creditors benefit from knowing the true characteristics of debtors, but moral hazard hampers direct IS between market participants (LELAND; PYLE, 1977), and verification by outside parties may be either costly or impossible (TOWNSEND, 1979). An important stream in financial theory considers that financial intermediaries provide the means to reduce the economic consequences of private information problems and transaction costs exchanges (DIAMOND; DYBVIG, 1983; DIAMOND, 1984; LEVINE et al. 2000).

The effect of IA over nonpayment behavior has been quantified by Karlan and Zinman (2009), who in their study about the South African credit markets, found that about 15% of default was due to private information problems. Literature suggests that IS may overcome adverse selection and reduce moral hazard, by raising borrowers' effort to repay loans (JAPPELLI; PAGANO, 2006) or by avoiding excessive lending when each borrower may patronize several banks (BENNARDO; PAGANO, 2007). Brown et al. (2009) showed that IS relates with improved availability and lower cost of credit to firms in transition economies.

In the case for P2P lending, there is very little assurance on the part of the lender that the borrower, having been possibly rejected by other financial intermediaries, will repay the loan (ZENG, 2013).

Weiss et al. (2010) found evidence that the screening of potential borrowers is a major instrument in alleviating adverse selection preventing the online market to collapse. Information availability improves lender screening and dramatically reduces the default rate for high-risk credits, but has little effect on low-risk loans (MILLER, 2015).

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Given the importance of credit rating, Moro et al. (2015) found that credit scoring is the main application used for predicting risk and supporting the loan approval process. In a joint effort with credit rating agencies, valuable information for understanding default behavior is shared with the lending communities by the platforms. Investors rely on credit scoring and the quality of the rating process in market-place loans, nevertheless “soft and self-reported” information also play important roles in their internal systems for decision making (KHWAJA, et al., 2009; FREEDMAN; JIN, 2014; DUARTE, et al., 2012; RAVINA, 2012).

Based on a statistical discrimination approach (PHELPS, 1972; ARROW, 1973), lenders have the opportunity to check the debtor´s credit grades, work and academic history, property, income to debt ratios and subjective information regarding use of credit, communication capacities and social ties in an attempt to separate payers from non-payers (RUIZ-UGARTE, 2010).

Moreover, Zhang and Liu (2012) in their study about the herding behavior among backers at Prosper found that investors infer the solvency of borrowers by observing decisions of other creditors, and by using the publicly observable borrower characteristics.

There is a somewhat richer literature explaining funding success in P2P loans, but this is by no means exhaustive (LEE; LEE, 2012; YUM, et al. 2012; LIN et al. 2013; GONZALEZ; LOUREIRO, 2014; ZHANG; LIU, 2012). For example, Herzenstein et al. (2008) showed that debtors’ financial strength, their listing and publicizing efforts and their demographic attributes, have an effect over the likelihood of funding success. In their study about P2P loan bidding, Weiss et al., (2010) showed that the most important factor used by lenders to allocate funds is the rating assigned by the P2P lending site.

The empirical evidence evaluating non-payment behavior in P2P lending is limited and geographically concentrated in developed countries. To the best of our knowledge there are no studies analyzing such behavior in Latin America, or Mexico specifically.

As per the literature, in recent studies about determinants of default behavior based on platforms like Lending Club (Serrano-Cinca et al. 2015), the authors tested the pertinence of variables that were classified according to the following categories:

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borrower assessment, loan characteristics, borrower characteristics, credit history, indebtedness and income related information. The factors explaining default were loan purpose, annual income, current housing situation, credit history and indebtedness and a model for predicting defaults was also estimated.

Emekter et al. (2015) found that variables like credit grade, debt-to-income ratio, FICO score and revolving line utilization played an important role in loan defaults while Dietrich and Wernli (2016) showed that borrower-specific factors such as its economic status significantly influence lender evaluations of the borrower's credit risk and thus the interest rates offered. Studies on the default behavior in the credit card market in Mexico, consider, as determinants, variables such as loan history, payment-income ratios and loan characteristics, factors that are usually included in parametric credit scoring models (García et al. 2015) and are consequent with the regulation and procedures established by the Mexican Banking Commission (CNBV, 2014).

3. DATA COLLECTION

As part of the application process, platforms collect quantitative and qualitative information about solicitants. Using credit rating algorithms and a minimum of human intervention, the platforms evaluate, approve and grade the loans if appropriate. As it is the norm in the credit industry, their model factors elements such as credit history, payment capacity and other pieces of information, some of them used traditionally in parametric credit analysis. After the loan has been formalized it is submitted to their on-line lending community. Data collected and included in the study is first described in Table 1.

Table 1: Variables provided for the study

Variables	*Description*	*Type*
RQAMT	Requested amount in pesos (original)[d]	Scale
Amount_less_100000	Is requested amount less than 100,000 MP? (Coded)[e]	Binary[a]
Approved	Was the loan approved? (Coded)[e]	Binary[a]
LTERM	Loan Term in months (original)[d]	Scale
Short_Term	Is Term less than 12 months? (Coded)[e]	Binary[a]
CONSDEBT	Is the purpose of loan to consolidate debt? (Coded)[e]	Binary[a]
BUSINESS	Is the purpose of loan finance business? (Coded)[e]	Binary[a]
CARLOAN	Is the purpose a car loan? (Coded)[e]	Binary[a]
HOME	Is the purpose of loan home improvements? (Coded)[e]	Binary[a]
EDUC	Is the purpose of loan education? (Coded)[e]	Binary[a]
Gender_of	Is the gender male? (Coded)[e]	Binary[a]
Marriage	Is the status of women married? (Coded)[e]	Binary[a]
AMOUNT_FUNDED	Actual amount funded (original)[d]	Scale
LRATE	Loan rate in % (original)[d]	Scale

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GRADE	7 categories for credit grade (A-G) (Coded)[e]	Ordinal[b]
Credit_Risk	Is credit grade Prime (C1 or less)? (Coded)[e]	Binary[a]
Default	**Coded DV**. Is loan delinquent or bad credit? (Coded)[e]	Binary[a]
Funding_Time	weeks elapsed from registration to payment (Coded)[e]	Scale
Success_Funding	Scale from 1 = a week through 6 = 2 months (Coded)[e]	Ordinal[c]
REFINANCED	Was the loan refinanced? (Coded)[e]	Binary[a]
INVESTORS	Number of investors per loan (original)[d]	Scale
Dec_INCOME	Self-reported monthly income (original)[d]	Scale
Paid_capital	Loan amortization (original)[d]	Scale
Balance	Amount- Paid_capital (Calculated)	Scale
PMT_Balance	Ratio of monthly payment to balance (Calculated)	Scale
Monthly_PMT	Monthly payment (original)[d]	Scale
PMT_Income	Ratio of payment to income (Calculated)	Scale
Credit_Mos	Loan number of months to date (time effect) (Calculated)	Scale
OWNAUTO	Owns car? (Coded)[e]	Binary[a]
OWNHOUSE	Owns home? (Coded)[e]	Binary[a]
GRAD_UG	Declared graduate or undergraduate studies (Coded)[e]	Binary[a]
Table 1 Continued		
METRO	Lives in the Mexico City Area? (Coded)[e]	Binary[a]
AGE	Age of applicant (Calculated)	Scale
Under_25	Is age under 25 years old? (Coded)[e]	Binary[a]
Male	Is the borrower male? (Coded)[e]	Binary[a]
Female	Is the borrower female? (Coded)[e]	Binary[a]
Previous_loan	Borrowed before in the platform? (Coded)[e]	Binary[a]
Default_mos	Months in delinquency (Calculated)	Scale
Days_default	Days in delinquency (Calculated)	Scale

Notes: [a]Binary response variables: 0=No, 1=Yes. [b]Ordinal 7 categories for Credit Grade from A down to G, A-grade being the safest. [c]ordinal 6 categories, from 1 being up to one week of funding time through 6 corresponding to more than 2 months to complete funding. [d](original) = variable directly in the sample. [e]Coded by researcher.

Our dataset includes 25,598 loan applications filed in the period from June 2012 through February of 2016. Loan approval rates depend on the product and are defined by management. Usually the approval strategy is designed around reducing risk by selecting only those applicants who are thought to have a very low risk of defaulting, thus the proportion accepted and the proportion of those accepted who subsequently default is inversely related. As per the information provided, the main cause for loan denial was the inability to meet one or more approval requirements. The descriptive statistics for variables in the data-set are presented in Table 2.

Table 2: Descriptive statistics for variables in the study

Variables	*M*	*SD*	*Range*	*n*
RQAMT	72,373	72,307	5,000-250,000	25,998
Ammount_less_100000	.78	.42	0-1	25,998
Approved	.05	.21	0-1	25,998
LTERM	27.42	9.98	7-120	25,598
Short_Term	.24	.43	0-1	25,598
CONSDEBT	.41	.49	0-1	25,998
BUSINESS	.23	.42	0-1	25,998
CARLOAN	.07	.25	0-1	25,998
HOME	.11	.32	0-1	25,998
EDUC	.06	.24	0-1	25,998
Gender_of	.65	.48	0-1	25,998

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Marriage	.64	.48	0-1	8,940
AMOUNT_FUNDED	74,254	59,906	0 – 250,000	1,161
LRATE	19.74%	3.76%	8.9%-27.9%	1,161
GRADE	4.27	1.27	1-7	1,161
Credit_Risk	.13	.34	0-1	1,161
Default	.11	.32	0-1	1,161
Funding_Time	3.21	2.19	0 – 6	1,161
Success_Funding	.29	.46	0-1	1,161
Table 2 Continued				
REFINANCED	.06	.23	0-1	1,161
INVESTORS	61.22	46.68	0 – 336	1,161
Multiple_Investors	.50	.50	0-1	1,161
DecINCOME	22,838	22,306	2,600 – 27,648	1,161
Paid_capital	18,285	22,110	0 – 250,000	1,161
Balance	55,968	54,558	0 – 250,000	1,161
PMT_Balance	.11	.56	0 -11.95	1,161
Monthly_PMT	3,498	2,729	352 -23,946	1,161
PMT_Income	.18	.11	.009 – 1.55	1,161
Credit_Mos	17.41	10.98	0 – 48	1,161
OWNAUTO	.67	.47	0-1	1,161
OWNHOUSE	.47	.50	0-1	1,161
property	.77	.42	0-1	1,161
GRAD_UG	.85	.35	0-1	1,161
METRO	.42	.49	0-1	1,161
AGE	36.67	.82	17-82	1,161
Over_60	.04	.19	0-1	1,161
Under_25	.05	.22	0-1	1,161
Male	.67	.47	0-1	1,161
Female	.33	.47	0-1	1,161
Previous_loan	.15	.36	0-1	1,161
Rural	.04	.19	0-1	1,161
Median_Income	.76	.43	0-1	1,161
Default_mos	7.88	7.92	.27 – 37.7	130
Days_default	236	237	0 – 1165	130

Notes: n = 25,598 refers to the total loan applications: n = 1, 1161 to approved loans, n = 8,940 to women in the sample and n =130 to defaulted loans.

Of total applicants, 65% are men and 35% women. The loan denial rate for men was 94.6% for men and 93.3% for women. Grouped by gender, in this section data collected through the platform is first described in Table 3.

Table 3: *Results of t-tests and Descriptive Statistics of variables in the dataset, grouped by gender*

	Men			*Women*			*95% CI for Mean*		
Variable	*M*	*SD*	*n*	*M*	*SD*	*n*	*Difference*	*t*	*df*
Loan characteristics									
RQAMT	74,772	73,461	16,650	67,910	69,893	8,948	5,033 , 8,690	7.36*	19,105
LTERM	27	10	16,650	27.61	9.88	8,948	-.54, -.03	-2.21*	18,565
LRATE	19.6%	3.8%	774	20.1%	3.7%	387	-.97% -.06%	-2.21*	1,159
INVESTORS	63	48	774	57	44	387	1.03, 12.42	2.32*	1,159
REFINANCED	5.3%	22.4%	774	7.0%	25.5%	387	-4.7%, 1.3%	-1.1	690
CONSDEBT	40.8%	49.1%	16,650	41.8%	49.3%	8,948	-2.3%, .3%	1.54	18,249
BUSINESS	24.1%	42.8%	16,650	21.5%	41.1%	8,948	1.5%, 3.6%	4.62*	18,930
CARLOAN	8.0%	27.2%	16,650	4.9%	21.6%	8,948	2.5%, 3.7%	10.02*	22,053
HOME	11.3%	31.7%	16,650	11.3%	31.7%	8,948	-.8%, .9%	.11	25,596
EDUC	5.5%	22.7%	16,650	7.2%	25.8%	8,948	-2.4%,-1.1%	-5.33*	16,404
Property									

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OWNAUTO	51.9%	50.0%	16,650	40.1%	49.0%	8,948	-1.1%, 1.3%	18.32*	18,615
OWNHOUSE	44.1%	49.7%	16,650	41.8%	49.3%	8,948	1.1%, 3.6%	3.58*	18,412
GRAD_UG	68.6%	46.4%	16,650	64.2%	47.9%	8,948	3.2%, 5.6%	7.11*	17,799
AGE	35.3	9.9	16,650	35.3	9.9	8,948	-.31, .21	-.35	24,629
METRO	37.7%	48.5%	16,650	34.7%	47.6%	8,948	1.8%, 4.3%	4.81*	18,593

*Notes: *p <.05. n = 16,650 for men and n = 8,948 for women.*

Loan purpose can be assimilated to perceived riskiness by lenders. As exhibited on Table 3, debt consolidation (CONSDEBT) is the most self-reported loan purpose, followed by financing business (BUSINESS). The Mexico City Metro Area (METRO) concentrates more than one third of total applications. The mean loan term (LTERM) in months is 27 and the non-weighted loan interest rate charged (LRATE) on average was 19.7%.

Results of the grouped samples t-tests show that mean requested amount RQAMT differ between men (M=74,772, SD =73,461) and women (M=67,910, SD=67,910) at the .05 level of significance (t = 7.36, df = 19, 105, n = 25,998, p < .05, 95% CI for mean difference is 5,033 to 8690). On average, women requested smaller loans than men, (6,962 pesos less). With respect to loan rates, variable LRATE also differs (M=19.96%, SD =3.8%) for men and (M=20.1%, SD=3.7%) for women at the .05 level of significance (t = -2.21, df = 1,159, n = 1,161, p < .05, 95% CI for mean difference is -.97% to .-06%). Female loan rates are quoted 50bp higher than those quoted for men. In the sample women are less likely to own property and in they do not concentrate in the Mexico City Area as men do.

In the platform, filings are classified over 21 categories ranging from A1 being the highest quality rating through G3, the lowest. In Table 4, we observe the following gender patterns of behavior after controlling for credit rating that is, collapsing the full scoring set into a subset comprising only 7 sub-categories, from A down to G, A-grade being the safest.

Table 4: Means and Standard Errors for variables: LRATE, LTERM and RQAMT grouped by Grade

	Men			*Women*		
Variable/grade	*M*	*SE*	*n*	*M*	*SE*	*n*
LOAN RATE						
A	9.65%	.16%	28	10.23%	.29%	9
B	13.31%	.12%	41	13.40%	.18%	16
C	16.04%	.07%	133	16.05%	.10%	66
D	19.07%	.05%	229	19.02%	.08%	111
E	21.87%	.06%	233	21.83%	.07%	107
F	24.68%	.07%	102	24.78%	.09%	68
G	26.90%	2.1E-17%	8	27.40%	.17%	10
LOAN TERM						

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A	30.00	1.799	28	32.00	2.828	9
B	33.65	.861	41	32.25	2.112	16
C	30.56	.704	133	30.67	1.042	66
D	30.48	.573	229	29.46	.885	111
E	29.74	.591	233	30.30	.851	107
F	33.46	1.442	102	29.29	1.157	68
G	33.00	3.000	8	29.90	5.740	10
Amount						
A	120,464.30	13,867.62	28	136,666.70	30,092.45	9
B	91,560.98	10,705.65	41	101,187.50	16,825.13	16
C	83,630.08	5,391.32	133	93,878.79	9,471.35	66
D	93,310.04	4,467.80	229	80,666.67	6,551.46	111
E	101,055.80	4,872.76	233	84,943.93	6,651.94	107
F	129,098.00	7,910.49	102	105,147.10	10,590.73	68
G	140,375.00	19,858.37	8	112,600.00	25,800.60	10

Notes: Credit rating (Grades) collapse the full scoring set (21 categories) into a subset comprising only 7 sub-categories, from A down to G, A-grade being the safest. N = 1,161 loans approved.

As can be observed in Table 4, for loans of the same quality, women in general pay higher rates and borrow greater amounts than men, especially at the safest categories.

Defaulted loans are those that are charged-off, refinanced and/or late in payment. Good status loans are loans that are fully paid or current in payment schedule. For that matter the rate of default in this article is defined as: $\frac{\text{Defaults}}{\text{Loans approved}}$.

Default is the dependent variable (**_DV_**) in this study and it´s a binary response coded variable which is equal to 1 if the loan has defaulted and 0 otherwise. The simple mean rate of default for men is 11.76% and 10.07% for women. Classified by grade, as can be observed in Table 5, there are no significant differences by gender in actual default rates.

Table 5: Results of t-test and Descriptive Statistics for Default by gender, classified over Credit Grades

	Men			_Women_				
Outcome	_M_	_SE_	_n_	_M_	_SE_	_n_	_t_	_df_[a]
A	0	0	28	0	0	9	--	--
B	.049	.03	41	.063	0.25	16	.19	24
C	.070	.02	133	.030	0.02	66	-1.64	187
D	.122	.02	229	.100	0.03	111	-.65	236
E	.120	.02	233	.150	0.03	107	.73	189
F	.210	.04	102	.130	0.04	68	-1.27	159
G	.125	.13	8	.000	0.00	10	-1.00	7

Notes: adf: Satterthwaite's degrees of freedom. *p < .05

4. RESEARCH HYPOTHESES AND TEST METHODOLOGY

The research question addressed in this study is what are the elements that could help lenders characterize default risk in P2P loans? Given the fact that on-line

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investors are exposed to the totality of credit risk, besides credit scoring, lending, web-sites must provide pertinent information for overcoming the adverse effect of IA. Default probabilities by grade are not directly observed by backers therefore it is believed that they can rationally benefit from statistical discrimination by factoring in information believed to be correlated with default probabilities.

From a set of collected variables, mostly available to the on-line community, this study will attempt to identify, which of them are pertinent for assessing default rates. Previous studies on P2P non-payment behavior, at first, guide our variable selection process (EMEKTER et al. 2015; GARCÍA et al. 2015; WEISS et al., 2010; SERRANO-CINCA et al. 2015).

In our study, bearing in mind our lenders perspective, and the fact that the platform has already factored in a scoring model all the information collected, we will be testing whether variables related to loan characteristics, demographics, loan performance in the platform, credit purpose, income and debt servicing capacity, besides credit scores are correlated with default comportment in the sample.

The first hypothesis that would be tested is: Grades, as derived from the platform´s credit scoring model are considered determinants of default behavior in our P2P lending case.

The second hypothesis that follows, in general is: Lenders benefit from statistical discrimination in the sense given by Schwab (1986), by factoring variables related to loan and demographic characteristics of the applicants: CONSDEBT, PMT_Income, Female, Paid_capital, OWNHOUSE, Credit_Mos (time effect), REFINANCED in addition to credit scoring variables (GRADE), as provided by the lending web-site. In this case, the benefit for investors resides in attaining a better knowledge of non-payment behavior by debtors.

The third hypothesis is: The gender variable, specifically if the loan applicant is a female, is believed to be correlated with default behavior. Therefore, lenders may benefit from screening loans by sex, using taste-based discrimination. To be able to identify the case discrimination effect of gender we need to control credit quality. This hypothesis would be also tested after having controlled by GRADE derived from the platform’s credit scoring model.

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Our hypotheses testing rely on the reduced form model: $y_i = \pi_i + \varepsilon_i\ ,\quad i = 1, \ldots, n,$ Where π_i is the expected value of $\mathcal{Y}$ given $(\mathcal{X}_1 = x_{i1},\ \mathcal{X}_2 = x_{i2}, \ldots, \mathcal{X}_p = x_{ip})$. In our case $\mathcal{Y}$ is the probability of default as a function of a set of available information about the borrower. Following Aguilera et al. (2006), the logistic regression model used for testing the hypotheses is defined in the following way: Let $X_1, X_2, \ldots, X_p$ be a set of continuous or categorical observed variables and let us consider n observations of those variables represented in the matrix $\mathcal{X}$= $(X_{ij})_{n \times p}$. Let Y = $(y_1, \ldots, y_n)'$ be a sample of a binary response variable $\mathcal{Y}$, associated with the observations in $\mathcal{X}$, where $y_i \in \{0,1\},\ \ i = 1, \ldots, n$. The logistic regression is defined by: $y_i = \pi_i + \varepsilon_i\ ,\quad i = 1, \ldots, n,$ (1) Where π_i is the expected value of $\mathcal{Y}$ given $(\mathcal{X}_1 = x_{i1},\ \mathcal{X}_2 = x_{i2}, \ldots, \mathcal{X}_p = x_{ip})$ and is modelled as: $\pi_i = P\{\mathcal{Y} = 1 | \mathcal{X}_1 = x_{i1}, \ldots, \mathcal{X}_p = x_{ip}\} = \frac{\exp\{\beta_0 + \sum_{j=1}^{p} x_{ij}\beta_j\}}{1+\exp\{\beta_0 + \sum_{j=1}^{p} x_{ij}\beta_j\}}$, (2) where $\beta = \acute{\beta_0}, \acute{\beta_1}, \ldots, \acute{\beta_p}$ are the parameters defining the model and ε_i are the zero mean independent errors whose variances are: $Var[\varepsilon_i] = \pi_i(1 - \pi_i)$, $i = 1, \ldots, n)$. We define the logit transformation $l_i = \ln(\pi_i / (1 - \pi_i)),\ i = 1, \ldots, n$. Here $\pi_i / (1 - \pi_i)$ stands for the odds of response $\mathcal{Y} = 1$, for the observed value of $(x_i = x_{i1}, \ldots, x_p = x_{ip})$. The logistic regression model can be estimated as a generalized linear model (GLM), using the logit transformation as the link function. In matrix notation the logistic regression model can be expressed as: $L = \mathrm{X}\beta$, where $L = (l_1, \ldots, l_n)'$ is the vector of logit transformations as defined above, ($\beta = \beta_0, \beta_1, \ldots, \beta_p)'$ is the vector of parameters and X=$(\mathbf{1}|\mathcal{X})$, the design matrix, with 1=(1,…,1)´ is a n-dimension vector of ones.

When a binary response outcome is modeled using logistic regression, it is assumed that the logit transformation of the outcome has a linear relationship with the predictor variables. Thereby the relationship between the response variable and its covariates is interpreted through the odds ratio from the parameters of the models.

In equation (2), the exponential of the jth parameter $(j = 1, \ldots, p)$, is the odds ratio of success $\mathcal{Y} = 1$, when the jth predictor variable is increased by one unit,

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maintaining the other predictors constant. That is the exponential of the jth parameter of the logistic regression model gives the multiplicative change in the odds of success.

The transformation from probability to odds is a monotonic transformation, meaning the odds increase as the probability increases. The logistic model will be estimated by the maximum the method and its goodness of fit assessed through the Hosmer and Lemeshow test (HOSMER; LEMESHOW, 1989).

As stated before, the dependent variable (DV) in our regressions is Default, a coded binary response variable which is equal to 1 if the loan has defaulted and 0 otherwise. As it is the case, the hypotheses in this research can be tested by the estimated values adopted by the vector of parameters ($\beta = \beta_0, \beta_1, \dots, \beta_p$)´. The null hypothesis states that $\acute{\beta_i} = 0$, or there is no linear relationship in the population.

Rejecting such a null hypothesis implies that a linear relationship exists between X and the logit of Y. Moreover, in our case, if $\acute{\beta_i} \neq 0$, the corresponding variable X_i is considered to have an effect on the probability of default. The value of the coefficient $\acute{\beta}$ determines the direction of the relationship between X and the logit of Y. When $\acute{\beta_i} > 0$ larger (or smaller) X values are associated with larger (or smaller) logits of Y.

Conversely, if $\acute{\beta_i} < 0,$ larger (or smaller) X values are associated with smaller (or larger) logits of Y (Peng et al. 2002). For that matter if the parameter in the regression is positive, the probability of success increases, and when it´s negative, decreases (Hosmer & Lemeshow, 1989). In our case the (+/-) signs on the parameters would indicate that the variables determines that the loan has better (worse) chances of defaulting.

5. ESTIMATION RESULTS

From a lender's perspective, the most important concern in P2P lending is to better understand non-payment behavior. It is crucial to be able to screen credits using borrower´s characteristics available, which correlate with default probabilities. In order to test our hypotheses and before we proceed to the estimation results, we implement non-parametric tests to identify significant differences between defaulted

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and good loans. After that the model estimates default probabilities using logistic regression 1.

In Table 6 we present the results of the non-parametric tests, summarizing the differences between good and bad loans. In the sample, loan characteristics as expressed by values of variables: RQAMT, LTERM, LRATE, GRADE, REFINANCED, INVESTORS, Decl_INCOME and Credit_Mos are statistically different at the 1% significance level. Specifically, the interest rate and the average loan term are higher on a delinquent loan, while amounts borrowed and loan amortization are smaller. A greater number of investors back good loans, and the time effect is related to bad loans. Interestingly enough, declared monthly income is higher on average on delinquent loans, suggesting the need for validating such information as provided by the platform.

Table 6: Nonparametric test of differences between good loans and defaulted loans (June 2012–Feb 2016)

Variables	Defaulted Loans	Good Loans	Chi-Squared	Significance	df
RQAMT*	Lower	Higher	4.43	.04	1
LTERM*	Higher	Lower	4.59	.03	1
LRATE*	Higher	Lower	14.14	.00	1
GRADE*	Higher	Lower	14.98	.00	1
REFINANCED*	Higher	Lower	42.14	.00	1
INVESTORS*	Lower	Higher	8.75	.00	1
DeclINCOME*	Higher	Lower	24.73	.00	1
PAID CAPITAL	Lower	Higher	.58	.45	1
Credit Mos* (time effect)	Higher	Lower	63.76	.00	1

*Notes: *p <.01. All the variables except Paid Capital are significantly different at the 1% level based on the Chi-Square statistic value of the Kruskal Wallis Test.*

For the purpose of testing our hypotheses, in Table 7 we report the results from the logistic regression, having *Default* as the ***DV***. All the estimated coefficients are significant at the 1% level, with the exception of GRADE, CONSDEBT and Female which are significant at the 5% level.

Table 7: Summary of Logistic Regression Analysis for Variables Predicting Default Probabilities

Predictor	*B*	*z*	*P>z*	e^{B} *(Odds Ratio)*	e^{BSDX}	*SE*
Approved Loans						
Previous_loan	- .715***	- 4.87	0	0.18	.543	.352
GRADE	.226**	2.204	.028	1.253	1.331	.102
CONSDEBT	-.462**	- 2.134	.033	.63	.794	.217
PMT_Income	2.818***	2.782	.005	16.747	.359	1.013
Female	-.499**	- 2.13	.033	.607	.79	.234
Paid_capital	-.0001***	- 6.838	0	1	.234	.000

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OWNHOUSE	.497***	2.285	.022	1.644	1.282	.218
Credit_Mos	.136***	10.587	0	1.146	4.458	.0129
REFINANCED	2.555***	7.338	0	12.877	1.823	.348
constant	- 5.128	- 9.877	0			.519

*Notes: *p < .05. **p < .01. ***p < .001.*

The Hosmer and Lemeshow test (1982) confirms that the model is adequate in explaining the status of loans with a chi-square value of 12.56 (*df=8*), and a significance of .128. Multi-collinearity is not significant since all SE´s of coefficient estimates are smaller than 2. McFadden R^2 for the binary regression model is 25% and Nagelkerke´s R^2 is 32%. The percentage for loans that are correctly classified is 84.53 and a test for misspecification using STATA´s™ *linktest* was not significant at the 5% level. Hence, the probability of default for a typical loan in the platform can be obtained through the following equation 3:

$$PD = B_o + B_1 Previous\ Loan + B_2 GRADE + B_3 CONSDEBT + B_4 PMT_{Income} + B_5 Female + B_7 Paid_{capital} + B_8 OWNHOUSE + B_9 Credit_{Mos} + B_{10} REFINANCED + \varepsilon_i \quad (3)$$

The first hypothesis tested is the one about the appropriateness of *GRADE* as a determinant of delinquent behavior. In this case B2 is statistically different from 0 at a significance level of 1%, hence we reject the null hypothesis and consider the platform' s credit scoring variables as determinant of default in our case. Our results thus far suggest that the effect of *GRADE* over default rates is positive. Specifically for this sample, given that the variable Grade ranges from A=1 down to G=7, for a one unit increase in the GRADES score we expect to see about a 25.3% in the odds of becoming a defaulted loan.

The second hypothesis tests the importance of variables related to loan and borrower´s characteristics, which beside the credit score, are available to lenders. In Table 8 we present the nine predictor variables considered to be the determinants of default for our case, as well as their effect over the odds ratio.

Table 8: Predictor variables, coefficients and odd ratios, ordered by effect on loan default

Predictor	*B*	*e^B (Odds Ratio)*	*effect over odds*
Approved Loans			
PMT_Income	2.818***	16.747	*Increase*
REFINANCED	2.555***	12.877	*Increase*
OWNHOUSE	.497***	1.644	*Increase*
GRADE	.226**	1.253	*Increase*
Credit_Mos	.136***	1.146	*Increase*
Paid_capital	-.0001***	1	*Reduce*
CONSDEBT	-.462**	.63	*Reduce*
Female	-.499**	.607	*Reduce*
Previous_loan	- .715***	.18	*Reduce*
constant	-5.128		

*Notes: *p < .05. **p < .01. ***p < .001.*

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As displayed in Table 8, on one hand, the most important determinants for increasing the odds of loan default, besides the credit score, are those related to the ratio of monthly payment to income and having been refinanced on the same platform. On the other hand loan purpose and being a female applicant reduce the odds of loan default.

For the third hypothesis relating the effect of gender on loan default, after controlling by GRADE, we present the results in Table 9.

Table 9: Odds ratios, standard errors, Z values, significance and Pseudo R estimates for predictor variables of loan default

Predictors/Grade	e^B *(Odds Ratio)*	SE	Z	P>z	PseudoR
Grade A					
No cases					
Grade B					1.0
Previous_loan	predicts failure completely				
Table 9 Continued					
Grade C					.32
*Previous_loan***	.05	.07	-2.05	.04	
GRADE	1.00	(omitted)			
CONSDEBT	.54	.40	-.83	.41	
*PMT_Income**	.58	3.98	-.08	.94	
*Female**	.21	.19	-1.75	.08	
*Paid_capital****	1.00	.00	-2.77	.01	
OWNHOUSE	.61	.43	-.71	.48	
*Credit_Mos****	1.21	.06	3.87	.00	
*REFINANCED***	95.85	201.45	2.17	.03	
_cons	.03	.04	-2.95	.00	
Grade D					.26
*Previous_loan****	.10	.08	-2.8	.01	
GRADE	1.00	(omitted)			
*CONSDEBT**	.47	.19	-1.85	.06	
PMT_Income	5.37	12.00	.75	.45	
Female	.49	.22	-1.59	.11	
*Paid_capital****	1.00	.00	-3.52	.00	
*OWNHOUSE****	3.98	1.67	3.29	.00	
*Credit_Mos****	1.14	.03	5.37	.00	
*REFINANCED****	25.92	21.93	3.85	.00	
_cons	.02	.01	-6	.00	
Grade E					.36
*Previous_loan****	.08	.08	-2.8	0	
GRADE	1.00	(omitted)		--	
CONSDEBT	.83	.19	-1.85	.66	
*PMT_Income****	397	12	.75	.007	
Female	1.15	.22	-1.59	.74	
*Paid_capital ****	.99	.00	-3.52	0	
OWNHOUSE	.73	1.67	3.29	.47	
*Credit_Mos ****	1.21	.03	5.37	0	
*REFINANCED***	4.98	21.93	3.85	.013	
_cons	.01	.01	-6	0	
Grade F					.25
Previous_loan	.67	.40	-.67	.503	
GRADE	1.00	(omitted)			

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CONSDEBT *	.43	.21	-1.69	.091
*PMT_Income***	*140.70*	*350.21*	*1.99*	.047
Female *	*.41*	*.21*	*-1.73*	*.084*
Paid_capital	*.99*	*.0000135*	*-1.63*	*.102*
OWNHOUSE	*1.45*	*.70*	*.78*	*.435*
Credit_Mos ***	*1.11*	*.03*	*3.92*	*0*
*REFINANCED****	34.00	25.15	4.77	0
_cons	.01	.009	-4.14	0
Grade G				
CONSDEBT	predicts failure completely			

*Notes: *p < .05. **p < .01. ***p < .001. . GRADE collapses 21 scores into 7 subcategories, from A down to G, A-grade being the safest.*

Regarding gender and consequent with the results found by Miller (2015), being a female applicant in the context of the Mexican P2P ecosystem, is relevant in positively determining loan default only in credit scores C and F, therefore there is no conclusive evidence that lenders might benefit by screening default behavior based on gender, at equal loan characteristics in this sample. Nonetheless after calculating survival times in months the median for women is 9.2 months and 5.4 for men.

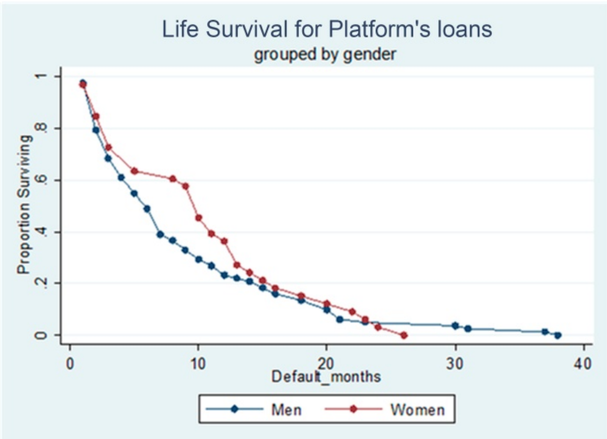

Figure 1: Life survival times by gender. This figure shows the proportion of surviving loans with the passage of time for men and women.
Own elaboration from the platform´s s sample

As displayed in table 10, evidence confirms that overall, women have better default behavior when controlling for loan quality as measured by loan survival alone, in a consistent with results derived from the estimation of our testing model.

Table 10: Survival times by gender and GRADE

Gender	GRADE	Loan quality	Median Survival times
Men		B*	20.0
		C	6.5
		D	3.1
		E	5.3
		F	4.9
		G*	6.8
Women		B	15.3

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C*	12.0
D*	4.9
E*	9.5
F*	12.2

Notes: Median survival times in months. Grade = Higher Survival time by gender*

6. CONCLUDING REMARKS

This research has investigated the effect of variables related to loan and borrower´s characteristics in addition to credit scores in determining default behavior in P2P lending in Mexico. Moreover, it tested whether investors might benefit from screening loan applicants by loan and demographic characteristics including sex after controlling for loan quality, even though gender information is not shared explicitly with lenders by the platform. To this end we have used a dataset provided by one platform with nation-wide presence in Mexico. The sample contained collected variables from loan applications and public information mostly available to on-line investors.

The results showed that information provided by the platform is relevant for analyzing credit risk, yet not conclusive at determining non-payment conduct. In congruence with the literature, loan quality as measured, on a reverse scale, by the platform´s credit scores is positively associated with default performance. In addition the most important determinants for increasing the odds of default are the payment-to-income ratio and having refinanced the terms of the loan on the same platform.

On the contrary loan purpose (a measure of perceived riskiness) and being a female applicant reduce such odds. Regarding gender, there is no conclusive evidence that, under equal credit characteristics, lenders might benefit by screening default behavior by sex in this sample. Moreover, consistent with previous studies by Miller (2015), being a female applicant is relevant in positively determining loan default only in riskier loans. However it was found that given equal credit ratings women have longer loan survival times than men, hence they have better default behavior, as measured by loan survival times alone.

To the best of our knowledge, this research is one of the first studies about P2P lending in Latin America, raising the possibility of including further disclosed information and analyzing other cases in the region for comparison purposes.

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There are important implications of these findings for lenders, researchers and policy makers. Firstly this study contributes in general to the CF literature and provides further understanding about the P2P ecosystem in Mexico.

Secondly it provides evidence that the on-line community in Mexico might benefit from more transparency and information sharing in the P2P lending process and highlights the importance of regulation, data generation and disclosure as catalysts for this activity in the country. Thirdly, it leverages the discussion around creditworthiness and growth potential of women in an emergent economy.

Due to the fact that on-line financiers bear all the credit risk, the natural next step of this study would be to attain a better perspective about the relationship between credit ratings and assigned interest rates, in order to have a clear picture of the risk-reward link in P2P lending.

There is no need to mention that this research was based on one platform in Mexico, notwithstanding the largest. Comparison with other platforms and enriching the available datasets are surely, tasks for the future. Nevertheless this effort can be considered as the first step towards further academic and institutional discussion about the topic.

REFERENCES

AGUILERA, A.; ESCABIAS, M.; VALDERRAMA, M. (2006). Using principal components for estimating logistic regression with high-dimensional multicollinear data. **Computational Statistics & Data Analysis**, v. 50, n. 8, p. 1905-1924.

AKERLOF, G. (1970). The Market for “Lemons”: Quality Uncertainty and the Market Mechanism. **Quarterly Journal of Economics**, n. 84, p. 488-500.

ALLEN, F.; SANTOMERO, A. (1997). The theory of financial intermediation. **Journal of Banking & Finance**, v. 21, n. 11, p.1461-1485.

ARROW, K. (1973). **The Theory of Discrimination**. in Ashenfelter, O, & A. Rees (Eds.), Discrimination in Labor Markets (p. 3-33). Princeton University Press, Princeton, NJ,

BACHMANN, A.; BECKER, A.; BUERCKNER, D.; HILKER, M.; KOCK, F.; LEHMANN, M.; FUNK, B. (2011). Online peer-to-peer lending-a literature review. **Journal of Internet Banking and Commerce**, v. 16, n. 2, p. 1.

BENNARDO, A.; PAGANO, M. (2007). **Multiple-bank lending, creditor rights and information sharing**. University of Salerno Mimeo.

BERGER, S.; GLEISNER, F. (2009). Emergence of financial intermediaries in electronic markets: The case of online P2P lending. **BuR-Business Research**, v. 2, n. 1, p. 39-65.

http://www.ijmp.jor.br v. 9, n. 1, January - March 2018
ISSN: 2236-269X
DOI: 10.14807/ijmp.v9i1.537

BROWN, M.; JAPPELLI, T.; PAGANO, M. (2009). Information sharing and credit: Firm-level evidence from transition countries. **Journal of Financial Intermediation**, v. 18, n. 2, p. 151-172.

CAVALLUZZO, K.; CAVALLUZZO, L.; WOLKEN, J. (2002). Competition, Small Business Financing, and Discrimination: Evidence from a New Survey. **Journal of Business**, n. 75, p. 641-680.

CNBV. (2014). **Normatividad CNBV**. Retrieved July 20, 2016, from http://www.cnbv.gob.mx/SECTORES-SUPERVISADOS/SOCIEDADES-DE-INVERSION/Paginas/Normatividad.aspx

DIAMOND, D. (1984). Financial intermediation and delegated monitoring. **The Review of Economic Studies**, v. 51, n. 3, p. 393-414.

DIAMOND, D; DYBVIG, P. (1983). Bank runs, deposit insurance, and liquidity. **The journal of political economy**, p. 401-419.

DIETRICH, A.; WERNLI, R. (2016). **What Drives the Interest Rates in the P2P Consumer Lending Market?** Empirical Evidence from Switzerland. Institute of Financial Services IFZ. Lucerne University of Applied Science working papers.

DORFLEITNER, G.; LEIDL, M.; PRIBERNY, C.; VON MOSCH, J. (2013). What determines microcredit interest rates? **Applied Financial Economics**. v. 23, n. 20, p. 1579-1597.

DUARTE, J.; SIEGEL, S.; YOUNG, L. (2012). Trust and Credit: The Role of Appearance in Peer-to-Peer Lending. **Review of Financial Studies**, n. 25, p. 2455-2484.

EMEKTER, R.; TU, Y.; JIRASAKULDECH, B.; LU, M. (2015). Evaluating credit risk and loan performance in online Peer-to-Peer (P2P) lending. **Applied Economics**, v. 47, n. 1, p. 54-70.

FREEDMAN, S.; JIN, G. (2014). The information value of online social networks: Lessons from Peer-to-Peer lending (No. w19820). **National Bureau of Economic Research**.

GALLOWAY, I. (2009). Peer-to-peer lending and community development finance. **Community Investments**, v. 21, n. 3, p. 19-23.

GARCÍA, J.; GARCÍA, M.; VENEGAS, F. (2015). **Administración del riesgo crediticio al menudeo en México**: una mejora econométrica en la selección de variables y cambios en sus características. Contaduría y Administración.

GONZALEZ, L.; LOUREIRO, Y. (2014). When can a photo increase credit? The impact of lender and borrower profiles on online peer-to-peer loans. **Journal of Behavioral and Experimental Finance**, n. 2, p. 44-58.

HAND, D.; HENLEY. (1997). Statistical classification methods in consumer credit scoring: a review. **Journal of the Royal Statistical Society: Series A (Statistics in Society)**, v. 160, n. 3, p. 523-541.

HERZENSTEIN, M.; ANDREWS, R.; DHOLAKIA, U.; LYANDRES, E. (2008) The democratization of personal consumer loans? Determinants of success in online peer-to-peer lending communities. **Boston University School of Management Research Paper**, v. 14, n. 6.

ISSN: 2236-269X
DOI: 10.14807/ijmp.v9i1.537

HOSMER,D.; LEMESHOW,S. (1989) **Applied regression analysis**. New York: John Wiley

HULME, M.; WRIGHT, C. (2006). **Internet based social lending**: Past, present and future. Social Futures Observatory, n. 115.

ITURBIDE, L.; CANFIELD, C. (Octubre de 2015). Una perspectiva académica sobre la participación en proyectos de financiamiento colectivo: las prácticas de Crowdfunding en México. **Reporte Macroeconómico de México**, v. 6, n. 9, p. 25.

JAPPELLI, T.; PAGANO, M. (2006). **Role and effects of credit information sharing**. In: BERTOLA, G.; DISNEY, R.; GRANT, C. (Eds.), Economics of Consumer Credit (p. 347-371). Cambridge: MIT Press, Cambridge.

KARLAN, D.; ZINMAN, J. (2009). Observing unobservables: Identifying information asymmetries with a consumer credit field experiment. **Econometrica**, v. 77, n. 6, p. 1993-2008.

KHWAJA, A.; IYER, R.; LUTTMER, E.; SHUE, K. (2009). **Screening in New Credit Markets**: Can Individual Lenders Infer Borrower Creditworthiness in Peer-to-Peer Lending? Kennedy School of Government, Harvard University. HKS Faculty Research Working Paper Series RWP09-031.

LEE, E.; LEE, B. (2012). Herding behavior in online P2P lending: An empirical investigation. **Electronic Commerce Research and Applications**, v. 11, n. 5, p. 495-503.

LELAND, H.; PYLE. (May de 1977). Informational Asymmetries, Financial Structure and Financial Intermediation. **The Journal of Finance**, n. 32, p. 371-387.

LEVINE, R.; LOAYZA, N.; BECK, T. (2000). Financial intermediation and growth: Causality and causes. **Journal of monetary Economics**, v. 46, n. 1, p. 31-77.

LIN, M.; PRABHALA, N.; VISWANATHAN, S. (2013). Judging borrowers by the company they keep: Friendship networks and information asymmetry in online peer-to-peer lending. **Management Science**, v. 59, n. 1, p. 17-35.

MARKIDES, C. (2006). Disruptive innovation: In need of better theory. **Journal of product innovation management**, v. 23, n. 1, p. 19-25.

MILLER, S. (2015). Information and default in consumer credit markets: Evidence from a natural experiment. **Journal of Financial Intermediation**, v. 24, n. 1, p. 45-70.

MORO, S.; CORTEZ, P.; RITA, P. (2015). Business intelligence in banking: A literature analysis from 2002 to 2013 using text mining and latent Dirichlet allocation. **Expert Systems with Applications**, v. 42, n. 3, p. 1314-1324.

PAULY, M. (1974). Overinsurance and public provision of insurance: The roles of moral hazard and adverse selection. **The Quarterly Journal of Economics**, p. 44-62.

PENG, C.; LEE, K.; INGERSOLL, G. (2002). An introduction to logistic regression analysis and reporting. **The Journal of educational research**, v. 96, n. 1, p. 3-14.

PHELPS, E. (1972). The statistical theory of racism and sexism. **The American Economic Review**, v. 62, n. 4, p. 659-661

http://www.ijmp.jor.br v. 9, n. 1, January - March 2018
ISSN: 2236-269X
DOI: 10.14807/ijmp.v9i1.537

POPE, D.; SYDNOR. (2011). What's in a Picture? Evidence of Discrimination from Prosper. com. **Journal of Human Resources**, v. 46, n. 1, p. 53-92.

RAVINA, E. (2012). LOVE & Loans. Effect of Beauty and Personal Characteristics in Credit Markets. Columbia Business School. **The Working Paper, Finance and Economics**., NY.

RUIZ-UGARTE, A. (2010). **Lecciones de la crisis Subprime**: ¿Es la titulización una opción para los mercados de préstamos P2P y de microfinanzas? BBVA Global Trends Unit BBVA Global.

SCHOLES, M.; BENSTON, G.; SMITH. (1976). A transactions cost approach to the theory of financial intermediation. **The Journal of Finance**, v. 31, n. 2, p. 215-231.

SCHWAB, S. (1986). Is Statistical Discrimination Efficient? **The American Economic Review**, v. 76, n. 1, p. 228-234.

SERRANO-CINCA; GUTIÉRREZ-NIETO, B.; LÓPEZ PALACIOS, L. (2015). **Determinants of Default in P2P Lending**. PLoS ONE: e0139427. v. 10, n. 10.

STIGLITZ, J.; WEISS, A. (1981). Credit rationing in markets with imperfect information. **The American Economic Review**, v. 71, n. 3, p. 393-410.

TOWNSEND, R. (1979). Optimal Contracts and Competitive Markets with Costly State Verification. **J Econ Theory**, n. 21, p. 265-293.

WAN, Q.; CHEN, D.; SHI, W. (2016). Online peer-to-peer lending decision making: Model development and testing. **Social Behavior and Personality: an international journal**. v. 44, n. 1, p. 117-130.

WEISS, G.; PELGER, K.; HORSCH, A. (2010). **Mitigating Adverse Selection in P2P Lending–Empirical Evidence from Prosper**. com. Ruhr-University Bochum, Department of Economics. Bochum, Germany: Available at SSRN 1650774.

YUM, H.; LEE, B.; CHAE, M. (2012). From the wisdom of crowds to my own judgment in microfinance through online peer-to-peer lending platforms. **Electronic Commerce Research and Applications**, v. 11, n. 5, p. 469-483.

ZENG, R. (2013). Legal Regulations in P2P Financing in the US and Europe. **US-China Law Review**, n. 10, p. 229.

ZHANG, J.; LIU, P. (2012). Rational herding in microloan markets. **Management Science**, v. 58, n. 5, p. 892-912.