WP/18/03

What determine loan rate and default status in financial technology online direct lending? Evidence from Indonesia

Wimboh Santoso[1], Irwan Trinugroho[2*], Tastaftiyan Risfandy[2],
Muhammad Agung Prabowo[2]

We empirically investigate the determinants of loan rate and default status of online direct lending in the context of Indonesia by studying loans generated by three platforms. We confirm that loan-specific factors and borrowers-specific characteristics play an important role in the determination of loan rate and default status of online direct lending in the context of Indonesia. Moreover, following the formal regulation on peer-to-peer lending in 2016, the number of borrowers increase significantly much more than the number of lenders. The shortfall of supply then drives the increase of loan rate. We also find that each platform has specific business model and target. Therefore, there is a significant difference in loan rate and default status between each platform.

JEL Codes: E43, G23, L51.
Keywords: Financial intermediation, Financial technology regulation, peer-to-peer lending.

---

[1]Otoritas Jasa Keuangan (OJK), Indonesia.
[2]Faculty of Economics and Business, Universitas Sebelas Maret, Indonesia.
[*]Corresponding author: *irwan_t@staff.uns.ac.id*.
This paper is part of the 2018 research project funded by Otoritas Jasa Keuangan (OJK). The authors thank the participants at OJK International Research Seminar in October 14, 2018 for their valuable comments and suggestions. The findings and interpretations expressed in this paper are entirely those of the authors and do not represent the views of OJK. All remaining errors and omissions rest with the authors.

1. Background

Indonesian policymakers have made substantial efforts to promote small business lending over the past decade through the traditional banking system. Some affirmative programs have also been launched such as the *Kredit Usaha Rakyat*/ KUR (small-scale loans) dedicated to improve access to finance for micro and small enterprises which in turn is expected to boost economic development. The government has also established the National Strategy for Financial Inclusion launched by presidential decree in 2012 which now targeting a near doubling of the proportion of the population with bank accounts to 75% by end 2019. Those efforts have improved access of small firms to formal financial institutions, however, the barriers to small business financing still exist. A substantial number of underbanked households, as well as micro and small enterprises, are even still trapped in illegal predatory lenders or loan sharks[1] (Karsidi et al., 2015; Trinugroho et al., 2015).

Technological-based financial innovations have been rising significantly in most countries in the world including Indonesia over the last few years to ease in delivering financial services and to improve financial activities. It is in line with the growing level of internet and smartphone penetration which enables the potential for a digital transformation in many aspects including the financial sector. Recently, financial innovations driven by technological advancement (financial technology) are reflected in some forms such as digital (mobile and internet) payments, electronic money, crowdfunding, peer-to-peer lending, investment, financial aggregator, and financial advisor. In here, we focus on online direct (peer-to-peer/P2P) lending which could directly help improve access to financing for micro and small enterprises. P2P lending platforms facilitate direct lending from surplus spending units to deficit spending units in an online system (Milne and Parboteeah, 2016). The system could be considered to eliminate some intermediary processes normally happen in the traditional banking system due to the benefit from internet-based information processing. P2P lending has also been thriving substantially in Indonesia. According to the data in September 2018, 67 platforms have been registered in the Indonesia Financial Services Authority (OJK). Moreover, the channeled loans have been more than IDR 9 trillion (USD 600 million), with the average yearly growth is around 300%. The number of borrowers have been more than 1.4 million accounts while total lenders are more than 135 thousand accounts. In line with this, the growing need of access to financing from SMEs with low access to banks creates a large opportunity to P2P to grow even further. Thus, it is necessary to ensure consumer protection both for the borrowers and lenders regarding the safety of the transaction and investment and reducing fraud.

In this present paper, we empirically investigate the determinants of loan rate and default status of online direct P2P lending in the context of Indonesia. Furthermore, taking advantage of the regulation on online-based lending (POJK 77/2016), it enables us to examine the difference in

[1] Indonesian: *Rentenir*

loan rate and default status before and after the regulation. To the best of our knowledge, this is the first comprehensive research empirically investigates some issues related to P2Plending in Indonesia. Prior studies on P2P lending have been done in the context of the USA, China, Germany, and some other countries. We contribute to the existing literature on peer-to-peer lending in several ways. First, we use three P2P lending platforms in this study and it enables us to analyze the difference in loan rate and default status across the platform business model. Second, we provide evidence on the impact of regulatory change.

In general, we find that that loan-specific factors and borrowers-specific characteristics play an important role in the determination of loan rate and default status of online direct lending in the context of Indonesia. Following the formal regulation on P2P lending in 2016, the number of borrowers increases significantly much more than the number of lenders. The shortfall of supply then drives the increase of loan rate.

The rest of the paper is organized as follows: section 2 reviews the literature on peer-to-peer lending; section 3 explains the data and empirical strategy; section 4 discusses the empirical results; section 6 concludes the paper.

2. Literature review

Peer-to-peer platform technology enables direct lending between savers and borrowers in an online system (Atz and Bholat, 2016; Milne and Parboteeah, 2016). The first P2P lending was introduced in the US in 2005 with the introduction of Zopa. De Roure et al. (2016) explain that in Germany, it started in 2008 when the Auxmoney was established. It then has been growing rapidly and has significantly reduced the dependency of people with lower income in the US on payday loans which usually charge a higher interest rate on the channeled loans.

Basically, there two competing implications of this online direct lending mechanism. First, due to the transaction is directly done between surplus and deficit spending units, obviously it could eliminate the intermediation cost in the formal financial institutions. On the other hand, however, due to the information asymmetric between lenders and borrowers, it then creates the high loan rate to cover the risk premium. It is confirmed by the most significant theoretical development on the peer to peer lending which is the one introduced by De Roure et al. (2016). By assuming that financial institutions are risk neutral and focusing on the impact of peer-to-peer lending on the consumer credit market, they build a theoretical model in which there is a market served by financial institutions and P2P. They postulate that P2P lending charges a higher interest rate than traditional banks due to P2P lenders have riskier borrowers.

P2P lending has been of academic interest in recent years. One of the main focus in the P2P lending research is on the impact of borrower characteristics on the probability of obtaining a loan or the interest rate should be paid by the borrower (Prystav, 2016). In general, these studies could be classified on several categories: (1) personal information, (2) herding behavior, (3) social networks or social capital, (4) geographic differences, and (5) other factors. In the P2P lending, lenders have to make decision in the context of information asymmetry because they evaluate the applicants by themselves with very limited information. Therefore, certain personal characteristics of the borrowers could also affect lenders decision to give a loan or not (Jin et al., 2017). Pope and Sydnor (2011) investigate funding probability in the P2P lending by focusing on the borrower characteristics. They find significant discrimination against borrowers' color skin. Loan listing with blacks in the attached picture is 25 to 35 percent less likely to receive funding rather than those whites with similar credit profiles. They also find that the market discriminates somewhat against elderly and significantly overweight but in favor of women and those with significantly military involvement. Jin et al. (2017) investigate how potential borrowers' attractiveness influenced lenders' attitude toward borrowers' repayment behavior. They find that "beauty premium" phenomenon is present in online P2P lending and the lenders are more tolerant towards attractive borrowers' dishonest behavior.

Herding behavior is an individual's tendency to mimics the actions (rational or irrational) of a larger group. Individuals indeed would not necessarily make the same choice. However, when this phenomenon persists, individuals in a group can act collectively without centralized direction. In the online P2P loan, it could be a greater likelihood of bidding in auctions with more existing bids. Investigating one of the most prominent P2P platform in Korea, Lee and Lee (2012) find strong evidence of herding and its diminishing marginal effect as bidding advances. In a similar vein, Herzenstein et al. (2011) provide evidence of strategic herding behavior by lenders. At the point where the borrower has received full funding, lenders have a greater likelihood of bidding an auction with more bids, that is a 1% increase in the number of bid increases the likelihood of an additional bid by 15%. Herzenstein et al. (2011) conclude that although herding behavior exists in the P2P loan auctions, it could benefit bidders individually and collectively.

Some research has also highlighted the importance of social network or social capital in the P2P loan. Freedman and Jin (2017) examine whether social networks facilitate online markets from P2P lending websites. They find that borrowers with social networks are more likely to have their loan granted and obtain a lower interest rate. However, a negative side of social networks also applies, because most borrowers with social ties are more likely to pay late or default. Their findings overall suggest that lenders should be very careful on using the social network in analyzing borrowers' quality. This finding is also supported by Freedman and Jin (2011). The latter study focuses on the relation between the social network and information asymmetry in the P2P lending. By using the data from Prosper.com, Freedman and Jin (2011) find that the role of the social network can mitigate the information asymmetry but the effect depends on the institutional incentives. Chen et al. (2016) study the relationship between individuals' group social capital and their lending outcomes in the online P2P financial credit market. They find that both dimensions of group social capital influence lending outcomes, and specifically, the borrower's structural group social capital has a negative effect on their lending outcomes. Their results reveal that the borrower's general group social capital (group membership) helps improve the repayment performance and alleviate default probability when only the group rating mechanism was in place.

Another factor that has been of academic interest is the geographic differences. Atz and Bholat (2016) discuss how P2P lending has evolved as financial innovation. They focus on the geographical factors because there are longstanding concerns in the UK about the differences in access to finance between north and south of UK particularly London. They are not focusing on defaults rate since the industry is still growing and some argue that P2P lenders may manifest significant losses in the near future. Therefore, no reliable inferences about the riskiness of the industry can be made. They find that regions in the south of the UK are investing more than they borrow. They also find that variation in loan terms between regions is relatively low. Karlan (2007) finds that higher geographic proximity of the borrower in a group reduces the default risk. This is attributed to the fact that group monitoring is more active with greater geographic proximity.

Research in P2P lending has also evolved on the areas beyond above-mentioned categories. Dorfleitner et al. (2016) examine the relation of soft factors that are derived from the descriptive texts to the probability of successful funding and the default probability in P2P lending. They find that spelling errors, text length and the mentioning of positive emotion evoking keywords predict the funding of probability on the less restrictive of the platform which even accepts applicants without credit scoring. Chen et al. (2016) investigated the role of punctuation in the P2P lending market. They investigate how the amount of punctuation used in loan descriptions influences the funding probability, borrowing rate, and default. They show that the amount of punctuation is negatively associated with the funding probability and borrowing rate. Dietrich and Wernli (2016) investigate P2P consumer loans and the determinants of the loan rates in Switzerland by considering loan specific, borrower-specific and macroeconomic factors. They find that interest rates for loans are higher if the duration is longer, if the loan amount is larger or if there are more loans available in the same period. In the borrower specific, they find that the interest rate is lower when the borrower is a homeowner. They also find some indication of discrimination by the lenders. Swiss passport holders have a significantly lower interest rate than foreigners living in Switzerland. Greiner and Wang (2010) find that economic status is the major determinants of the likelihood of funding and the interest rate should be paid by the borrower. Economic status consists of credit grade, debt to income ratio, verified bank account, homeowner, and previous successful loan. Cai et al. (2016), by studying signaling theory, compare the effects of various signals on the successful funding in three models (first time borrowing, repeated borrowing without prior lending, and repeated lending with prior lending). Their results confirm the power of a list of signals from the borrowing request. They find that in those three models, the power of different signals varies significantly. The potential lenders make decisions differently between evaluating a repeated borrowing request and first-time borrowing request.

Some studies in P2P lending use prominent platforms for various purposes such as Prosper to study information value of online social network (Freedman and Jin, 2017) and strategic herding behavior (Herzenstein et al., 2011), and Lending Club in US and We.com in China to study credit risk assessment (Xia et al., 2017). Freedman and Jin (2011) find some important finding from their investigation on Prosper.com. Prosper lenders understand the ordinal difference on borrowers' credit grade but the adverse selection still exists because of the incomplete disclosure of the borrowers' credit history. Prosper lenders also do not fully understand the risk they faced on the internet. By also examining Prosper, Iyer et al. (2015) in their study find that Prosper lenders predict individuals' likelihood of defaulting on a loan with 45% greater accuracy that the borrowers' exact credit score (unobserved by lenders). Peer lenders even achieve 87% of the predictive power of econometrician who observes all standard financial information about borrowers.

3. Research method

3.1. Sample description

All of our data comes from *Otoritas Jasa Keuangan* (Indonesia Financial Services Authority) which has the authority to regulate financial technology including peer-to-peer lending in Indonesia. We use data of three P2P platform in Indonesia from the period of 2014 to 2018. These platforms are part of 64 platforms that has officially registered and monitored by the OJK until November 2018 (www.ojk.go.id). For the reason of data confidentiality, in this paper we name these platforms as ***Alpha***, ***Beta***, and ***Gamma***. The brief description of each platform is as follows.

Alpha is one of the pioneer P2P lending platforms in Indonesia with total loan granted more than IDR 600 billion. Until 2018, Alpha has served over 160,000 micro business and surprisingly it has less than 5% loan default. Focusing on the very small villages in Indonesia where most of the people do not have access to the banks, Alpha lend to micro businesses that need capital around IDR 3 million to expand their business. Most of their borrowers are people who operate their business from their own home. To select borrower candidate, Alpha develops credit scoring that combines and analyze borrowers' behavior, profile, and personality. For instance, grade A means that borrowers have a probability of payback their loan between 97,11% to 100%, grade B have 95%-97% success probability and so on. Better grade means a lower probability of default. This credit grade is offered to the investors. To be an investor in Alpha, people could just register in its website and provide a fund IDR 3 million. This fund could be used to finance more than one business.

Beta is another platform that provides a marketplace for lenders and borrowers. In Beta, people only need IDR 1 million to be an investor, smaller than Alpha. However, compared to Alpha, total fund disbursed to the borrowers has reached more than 1 trillion. This is because different to Alpha, Beta's borrowers could propose amount up to 2 billion. Therefore, it is different from

Alpha that mainly focuses on the micro business. Beta categorize its financing into invoice financing, online seller financing, and employee financing. Invoice financing is a funding activity that is carried out by pledging an ongoing invoice as a source of loan payments by the borrower. Online seller financing is short-term funding provided to sellers in one of the e-commerce Beta partners. Employee financing is financing mode for those works in a company that has an agreement with Beta.

Gamma offers online fast and direct financing to the borrowers. Gamma claims that the money could come directly into borrowers' account in 24 to 48 hours. Gamma focuses on micro-financing with the amount up to IDR 3 million. Until November 2018, Gamma has financed its borrower with the total amount more than 200 billion. Around 30% of Gamma's financing portfolio is used for SMEs while other portions are used for education, health, and consumption.

3.2. Baseline analysis

In this paper our main purpose is to investigate the determinants of interest rate and the probability of default the P2P lending platform. We construct two separate equations as follows.

... (1)

$$\mathcal{L}\mathcal{L} \qquad \ldots \qquad (2)$$

where *i* represent individual borrowers. The dependent variable is *Loan_Rate* and *Default_Status*. The former is a rate charged to its borrowers in P2P platforms while the latter is the status of the loan, whether it is successfully repaid by the borrowers or being default. Rate of loan is determined by the P2P online platform after examining all of the information from the borrowers. Therefore, each loan is rated with a grade that tries to capture the risk of default and thus investors (lenders) can make their choices (Serrano-Cinca et al., 2015). If the probability default of a proposed loan is high, the grade determined by the platform is low, and therefore the interest rate offered to the investors is high. Investigating loan rate and default status has been of academic interest in recent years (Dorfleitner et al., 2016; Wang et al., 2018).

Log_Amount is the amount of loan proposed by the borrower and accepted by the platform, in the logarithm form. Loan amount is one of the most important risk characteristics in P2P lending (Berger and Gleisner, 2009). The larger amount in general results in larger perceived default risk of the borrowers (Jin et al., 2019). P2P lenders may prefer to lend to the small amount rather than big amount because the lender is sensitive with the investment risk (Cai et al., 2016). The association between the loan amount and default risk therefore is predicted to be negative. *Log_Period* is the period of loan or number of days from the loan granted until the date of maturity (a day when the principal and all remaining interest is due to be paid) in the logarithm form. This is similar to maturity as in Dorfleitner et al. (2016) or loan term as in (Han et al., 2018). A longer period of the loan could imply higher perceived risk and it is avoided by the online lenders (Lee and Lee, 2012). This is because the P2P lending platform is developing and changing rapidly and therefore lenders will prefer short investment to reduce risk. However, a longer period of a proposed loan could also show a promising and well-planned project from an entrepreneur. Lenders might opt to a loan with the long period since it could give them interest rate payment for a longer time. This argument is also strengthened by (Han et al., 2018) who find that loan term is positively associated with a funding success.

Borrower characteristics are our focus in this paper as prior works highlight that economic status and demography of the borrowers are determinants of interest rate or default probability in P2P lending (Greiner and Wang, 2010; Xia et al., 2017). In this paper, we focus on borrowers' gender (*Woman*), marital status (*Married*), home ownership (*House*), degree of education (*Education*), monthly income (*Log_Income*), and age (*Log_Age*). *Woman* is a dummy variable equals to 1 if the borrowers are female and zero for male. Pope and Sydnor (2011) find that the probability for women to obtain a loan from the P2P lending market is more than men. It is because women are considered more attractive to obtain a loan than men. Moreover, Jin et al. (2017) argue that beauty premium phenomenon does present in online P2P lending. Therefore, woman borrowers are expected to have a lower interest rate and lower default probability.

Married is also a dummy variable equals to one if the borrowers are married. The marital status has also become researchers' focus recently (Chen, Huang, et al., 2016; Han et al., 2018; Serrano-Cinca et al., 2015; Xia et al., 2017). This is because the behavior of the married and unmarried borrowers could be different. One might argue that married borrowers will have a lower probability of default because they are considered to be more financially stable. Conversely, it could also be argued that married borrowers will be financially constrained because the profit from those people's business also has to be used to feed their family.

Education could be a signal of the borrowers' quality (Cai et al., 2016) and could increase the probability of getting the loan funded (Chen, Huang, et al., 2016). A negative sign from *Education* could be expected as borrowers with higher education levels could obtain a fund with lower interest rate and could also have a lower probability of default, as also empirically found in (Chen, Huang, et al., 2016; Dorfleitner et al., 2016). However, a person's success in a business is not always related to their formal degree. People with a higher degree might have lower business experience because most of their time is allocated for study. Those people indeed have low business experience. Information about the borrowers' economic status is commonly used by lenders to evaluate borrowers' ability to repay a loan (Greiner and Wang, 2010). Better economic status of the borrowers could reduce the interest rate of the borrower (Greiner and Wang, 2010) because it increases the perceived trustworthiness of the borrowers. Economic status could be reflected from the monthly income (*log_income*) and home ownership (*house*) of the borrowers. Home ownership could signal that a person is responsible and capable of handling loans such as mortgage (Berger and Gleisner, 2009; Greiner and Wang, 2010). Therefore, we expect that negative signs from *Log_Income* and *House* since better income and home ownership will help borrowers to secure better interest rate. Our prediction is also supported by work from Chenet al. (2016) that find a negative impact of home ownership on the loan interest rate.

Log_Age is the age of the borrowers. Prior study highlights that age plays a key role in determining loan success (Gonzalez and Loureiro, 2014). We expect a negative association between age of loan applicant and the interest rate because age is a clear signal of competence (Gonzalez and Loureiro, 2014). A borrower above 40 is perceived more competence and stable regarding their financial condition. This argument is also empirically supported by Han et al. (2018) who report a positive association between age and funding success. However, other research such as Pope and Sydnor (2011) highlight that market discriminates somewhat against the elderly. The lack of knowledge about information technology for older people could be a big barrier for them to compete in the current business situation especially in a developing country like Indonesia.

3.3. Further analysis: A regulatory perspective

Another objective of this research is to examine the differences in the risk premium before and after the formal regulation for P2P lending established. To investigate this issue, we extend our analysis by using the following equations.

… (3)

$L \; LL_L = \; +$

$_1 \; L \; - \; L \; 77_L + \; _2$

$- \; LL_L$

$+ \; _3 \; L \; 77$

$L \; - \; LL_L$

$+ \; _4$

$-$

$LL_L +$

$_5 \; - \; LL$

$_L +$

$_6 \; _L + \; _7$

$LLL \; _L$

$+ \; _8 \; LL_L +$

$_9 \; LL$

$_L +$

$_{10} \; -L \; LL$

$_L +$

$_{11} \; - \; _L$

$+LLL \ldots$ (4)

Reg_POJK77 is a dummy variable equals to one if the loan is granted to the borrower after the introduction of the formal regulation (POJK 77, December 2016) and zero otherwise. The impact of regulation on peer to peer lending is predicted to be lowering interest rate because of the monitoring effort of the financial regulator. This could expectedly minimize the opacity and enhance the transparency of the business. In addition, the regulation will also speed up the funding time because the lenders have more confidence to invest their money using the platform. In this further analysis, we also make interactions between regulation and some of our variable of interest: amount and interest. In the equation (3), we introduce *Reg_POJK77*Log_Amount*. When the regulation applied in the Indonesian P2P lending market, the amount of loan proposed by the borrower is predicted to be higher than before the regulation issued because borrower will be more confident to ask more money using online platform. More borrower will use online platforms because it is faster than conventional ways (bank) and the platforms generally do not require any collateral. We also introduce interaction variable *Reg_POJK77*Loan_Rate* in the equation (4). The existence of formal regulation will decrease the interest rate charged to the borrower and subsequently decrease the default probability.

4. Empirical results

4.1. Descriptive statistics

Table 1 presents the descriptive statistics of our sample. There are significant differences regarding the number of observations from three platforms. Alpha has more than 1 million observations that we can use in the analysis whereas Beta has only 6,951 observation and Gamma has 168,434 observations. Because of this discrepancy, in the regression analysis that we will present its result further, we do not combine the sample from three platforms. Instead, we will present them separately to see the differences from one platform to others. Another reason is that in Alpha there is no data about home ownership and education so that the merging these sample is not possible. The definition of each variable, particularly how to measure, is described in the bottom of the table.

From more than 1 million observations in Alpha, we could see that the loan default in Alpha is very low, only 0.3%. Beta and Gamma have 5.2% and 11.6% loan default respectively. These statistics suggest that the loan default of P2P lending business is considerably low. If we see the comparisons of loan rate from three platforms, Gamma which has the highest percentage of loan default also has the highest loan rate. Because Gamma focuses on short-period of lending, which is from 10 days to 90 days, its average yearly interest rate on loan reach 272%. In comparisons, Alpha and Beta have 28.8% and 20% yearly interest rate respectively, far from Gamma. Alpha and Gamma focus on a very small loan, ranges between IDR 0,5 million to IDR 13 million for Alpha and between IDR 1 million to 8 million for Gamma. Interestingly, it is the only Beta that focuses on both large and small loan. The maximum value of loan they give to the borrower is IDR 600 million whereas the minimum value is IDR 2 million. Both Alpha and Gamma give their loan for approximately one-year maximum and 2 or 3 months minimum.

Now we turn to the characteristics of borrowers. All of the borrowers from Alpha are a woman (see variable *Woman*) and most of them are married (see variable *Married*). This is different to Beta and Gamma who has approximately 50%-woman borrowers that most of them are also married. We do not have any information about home ownership and education level for Alpha. However, as we could see in the Table, most of the borrowers in Beta (70%) own a house but not for Gamma (26%). This is plausible because the amount given by Beta is considerably high compared to Alpha.

If we see from the borrowers' income, we may conclude that borrowers from Beta on average could be entrepreneurs with the average income almost IDR 20 million from their business activities. In comparison, the mean of borrowers' income in Alpha and Gamma are IDR 3.1 and 5.9 million respectively, possibly very small entrepreneurs or employees. The borrowers in average hold Undergraduate degree (Beta) and Senior High School degree (Gamma). Gamma is mostly used by young people, with the average age of borrowers 26 years old. This is different from Alpha and Beta that have borrowers in the age of 41 and 37 years old respectively.

4.2. Baseline result: Loan rate and borrower's characteristics

We will start this section by explaining how borrower characteristics impact loan rate and loan default. We present the result in Table 2. We find strong evidence that the amount of loan is negatively associated with the interest rate given by the platform to the borrowers. P2P lending platforms tend to give a higher rate for the smaller loan. This is because small business demanding for small-scale loan through P2P platforms tend to have higher business risk than a medium or large enterprise. The coefficient of Gamma is also bigger than Gamma because the latter gives its loan on a daily basis with higher interest rate than the former. This result is consistent with Cai et al. (2016) and Jin et al. (2019). A larger amount of loan is associated with a higher perceived risk of borrowers. Lenders in Indonesia is also sensitive with investment risk so that they prefer to lend with a smaller amount.

From Table 2, we observe that the loan period positively impact loan rate for Alpha, implying that borrowers will be charged with a higher interest rate for a loan with a longer period. Consistent with Lee and Lee (2012), because P2P lending business is growing rapidly and may change in the future, lenders prefer to lend in the shorter period to minimize risk. However, different results are obtained from Beta and Theta that shows a negative sign. This means that longer period of the loan, lower interest rate. A plausible argument behind this is that lenders could see a longer loan period as a well-planned project so that they choose loans with a longer period than a shorter period. This argument is also consistent with (Han et al., 2018).

We also find that gender matters on P2P lending rate especially for Beta. Woman tend to have a higher rate of interest compared to man. This result is different to prior works such as Jin et al. (2017) and Pope and Sydnor (2011) who find a positive effect of beauty premium on the funding success. Our different result could be because of the sample we use. In Indonesia, lenders and platforms might see that man is more experienced in a business or work. Since more than 80% of Indonesian population are Muslims, they have a view that it is the man that is obliged to work for their family while the woman is responsible for taking care their children and providing family's need in the home.

Marital status also matters in explaining interest rate given by the platform. It has a negative association for Alpha and Beta but a positive impact for Gamma. This different impact is not surprising because there is two arguments about this. In the onehand, married people could be more financially stable because wedding party and all of the things related to that is not cheap in the Muslim community as in Indonesia. On the other hand, married people have more responsibility because they have to provide all of the things for their spouse and children so that they are financially constrained.

Regarding the economic status of the borrowers, our result also consistent with previous studies (Berger and Gleisner, 2009; Greiner and Wang, 2010). People who have house given lower interest rate by Beta possibly because having house signals a responsibility and capability of handling loans such as a mortgage. Another view is that home owners could use their house as collateral when asking for a loan so that they are charged with the lower interest rate. In a similar vein, higher borrowers' income is also associated with lower interest rate as we find for platform Beta and Gamma. This is because higher-income borrowers indeed have a higher probability of payment rather than smaller-income borrowers.

Last, we find two results regarding the impact of borrowers' age on the interest rate. For platform Alpha and Gamma, negative sign means that older borrowers are related to lower interest rate. This is consistent with Gonzalez and Loureiro (2014) who argue that age is a clear signal of borrowers' competence. However, for Beta, our positive and significant result support Pope and Sydnor (2011) who highlight that market discriminate older people.

To sum up, we find that the impact of borrowers' characteristics on the interest rate charged to them is different from one platform to others. This is because each platform has their own specific business model and strategy. For instance, Gamma serves young people (26 years old on average) that just start their job or a business. For this reason, the rate of interest given to them is very high (272% in average for a year) and the period of the loan is very short (10 to 90 days) because these young people are considered as risky borrowers who are lack of experience. For young people, if they are married, Gamma consider that their risk profile increase because they have more duties. It implies to the positive and significant impact of variable *married* for Gamma. The result is different to what we find in Alpha and Beta who show the negative sign for variable *married.* Alpha and Beta's borrowers are 41 and 37 years old on average. When they are married, they are considered to be more mature and stable so that the interest rate charge to them are smaller. In this age, unmarried people are considered to be unmatured in the Indonesian culture.

4.3. Loan default and borrower characteristics

One of the most interesting parts from three platforms in this study is that their rate of default is low. As described earlier, all of the platforms have default rate less than 15%. This is interesting because, recall that they give the loan based on the data they upload to the website of the platform. In other words, platforms might not take any survey to the candidate prior accepting to publish their loan proposals in the platforms' marketplace. Our results from the regression of loan default on the borrower characteristics are displayed in Table 3. The first finding we would like to discuss in this Table is that loan rate positively impact the loan default. This evidence could be a suggestion for the platforms to be careful about the rate of interest they charge to the borrowers. If the rate is too high, the probability of default is high as well.

Next, we find a strong and positive relationship between the amount of loan granted and default status of the borrowers, consistent with Chen et al. (2016). This is reasonable because P2P lending mainly focuses on small business lending possibly with high-risk profile of borrowers. The platform should focus on small business with small-scale loans rather than alarge amount of loan. Loans with a longer period is positively associated with the default status especially in Beta and Gamma. This result is consistent with the assumption that longer loan period is associated with the higher perceived risk that should be borne by the lenders (Lee and Lee, 2012). However, for Alpha, the negative result might suggest that investors are optimistic about the performance of Alpha (recall that Alpha have less than 1% loan default) so that longer period of loan does not matter for them.

Table 3 also shows that woman borrowers in Beta and Gamma have a higher probability of default than men. It strengthens our explanation in the section before that woman in Indonesia are possibly less experienced (in managing money and business) compared to the man. Regarding marriage status, married borrowers significantly reduce the probability of loan default, especially for Beta. This platform focuses on a large amount of loan. It therefore suggests that married borrowers are more able to deal with large-scale of the loan. When the loan amount is low as in Alpha, married borrowers strengthen the probability of loan default. Borrowers who own a house is associated with lower default probability especially in the case of Beta. Since Beta also focus on a large amount of loan, home ownership could be a signal for the lenders that borrowers are capable of managing their loan repayments. For Gamma, a positive sign means that borrowers are in the emergency and looking for fast and simple funding (Gamma's loan characteristics).

We also find in Table 3 that borrowers having a higher degree of education significantly reduce the probability of loan default. This is not surprising because education is a signal of borrowers' quality (Cai et al., 2016) and the similar results have been found in some prior works (Chen, Huang, et al., 2016; Dorfleitner et al., 2016).

The impact of borrowers' income on loan default is different between Alpha and Beta. The impact is negative for Alpha, meaning that lower loan default is associated with borrowers with higher monthly income. However, for Beta, positive sign implies that high-income borrowers are more exposed to loan default. If we also link this evidence with the business model of each platform, we could get an answer of the different result. Compared to Beta with the average amount of loan IDR 60 million, Alpha is only IDR 3 million. A smaller amount of loan is usually for very small business with very high risk operated by the new entrepreneurs. In this case, an entrepreneur with a stable and high income would be better because it could mitigate the default risk. However, in the case of Beta, high-income borrowers would tend to borrow the higher amount of loan compared to low-income borrowers. Consequently, higher income-borrowers tend to have higher loan default, as shown by a negative sign from variable *log_income* in Table 3.

We also find the different result of the variable *log_age*. This variable shows a positive sign for Alpha and a negative sign for Gamma. Similar to what we have explained in the previous section, the mean of age of borrowers in Alpha is very different. In average, borrowers in Alpha is 41 years old while in Gamma is 26 years old. For Gamma, older borrowers are associated with lower default probability because this platform focuses on young entrepreneurs or people who just started their career. Older people will have a more stable income and financial condition. This result contradicts with Alpha showing that older borrowers will have higher loan default probability. Recall that all of the Alpha's borrowers are a woman. When they are getting old, they might need more money to fulfill their want.

4.4. The impact of regulation

Table 5 shows how regulation impacts borrowers' interest rate and default risk in P2P lending. We also find that the impact is different between platforms. For Alpha and Gamma, the impact is positive but for Beta, the impact is negative. The positive impact implies that the introduction of formal regulation by OJK in the late of 2016 significantly increases the loan rate of P2P platforms. This might be not in line with the expectation of OJK that is to increase financial inclusion. OJK expected that after the introduction of the formal regulations, unbanked people and SME could have access to the financial products. However, this evidence is not without reason. Following this formal regulation, the demand on the P2P lending significantly increase. The shortfall of supply drives the increase of borrowers' interest rate. Moreover, in the POJK 77, there is no specific regulation about the maximum (or minimum) interest rate charged to borrowers. This makes platforms have their privilege to set their interest rate based on the ratings they develop. OJK argued that limiting the interest rate is not necessary because P2P platforms are mushrooming now. Competition between platforms will then determine the market acceptable interest rate.

Table 6 demonstrates the links between loan default and regulation. The negative sign of *Reg_POJK77* suggests that the introduction of formal regulation decrease the interest rates charged to the borrowers. Because of the escalation of the competition between platforms, the rate of interest is offered competitively to the borrower candidates. The positive signs form the interaction means that the formal regulation could significantly decrease the negative impact of loan rate on loan default. It means that in the formally regulated market of P2P lending, platforms have the privilege to set their interest rate and the negative effect of high-interest rate is diminished by the existence of regulation. For instance, borrower candidate could think that it does not matter to borrow money with a high amount and high-interest rate. This view could jeopardize the stability of the borrower as well as the lender and platform. However, the regulation offset this negative impact so that the borrower candidate could have more confidence to borrow money through P2P platforms.

5. Conclusion

Financial technology, particularly P2P lending, has been growing significantly in Indonesia over the last few years. The channeled loans have been more than IDR 9 trillion (USD 600 million), with the average yearly growth is around 300%. Therefore, it could help the government target to accelerate the level of financial inclusion.

In addition, there are some issues to deal particularly with regard to the riskiness of P2P lending. In an empirical study, we find that the riskiness level of P2P lending in Indonesia is still high as reflected by high-interest rate. We also confirm that loan-specific factors and borrowers-specific characteristics play an important role in the determination of loan rate and default status of online direct lending in the context of Indonesia. Furthermore, each P2P lending platform in Indonesia has a specific business model and target. Therefore, there is a significant difference in loan rate and default status between each platform. In addition, my empirical result also shows that following the formal regulation on P2P lending (POJK No. 77/POJK.01/2016) in 2016, the number of borrowers increases significantly much more than the number of lenders. The shortfall of supply then drives the increase of loan rate

Those findings have some policy implications. First, to avoid predatory competition between P2P lending and traditional financial institutions, the possibility of linkage between financial institutions and P2P platforms have to be considered by the government and financial authority. Second, the high risk of P2P lending indicates that this lending has a problem of information asymmetric. Therefore, it is necessary to ensure consumer protection and business transparency both for the borrowers and lenders. Third, more reliable and standardized reporting of P2P lending platforms to the financial authority should be imposed.

References

Atz, U. and Bholat, D. (2016), *Peer-to-Peer Lending and Financial Innovation in the United Kingdom Peer-to-Peer Lending and Financial Innovation in,* No. 598, *Bank of England Staff Working Paper,* available at:https://doi.org/10.4234/9781315676579.

Berger, S.C. and Gleisner, F. (2009), "Emergence of Financial Intermediaries in Electronic Markets: The Case of Online P2P Lending", *Business Research*, Vol. 2 No. 1, pp. 39–65.

Cai, S., Lin, X., Xu, D. and Fu, X. (2016), "Judging online peer-to-peer lending behavior: A comparison of first-time and repeated borrowing requests", *Information and Management*, Vol. 53 No. 7, pp. 857–867.

Chen, X., Huang, B. and Ye, D. (2016), "The role of punctuation in P2P lending: Evidence from China", *Economic Modelling*, Elsevier, No. July 2016, pp. 1–10.

Chen, X., Zhou, L. and Wan, D. (2016), "Group social capital and lending outcomes in the financial credit market: An empirical study of online peer-to-peer lending", *Electronic Commerce Research and Applications*, Elsevier B.V., Vol. 15, pp. 1–13.

Dietrich, A. and Wernli, R. (2016), "What Drives the Interest Rates in the P2P Consumer Lending Market? Empirical Evidence from Switzerland", *SSRN Electronic Journal*, available at:https://doi.org/10.2139/ssrn.2767455.

Dorfleitner, G., Priberny, C., Schuster, S., Stoiber, J., Weber, M., de Castro, I. and Kammler, J. (2016), "Description-text related soft information in peer-to-peer lending - Evidence from two leading European platforms", *Journal of Banking and Finance*, Elsevier B.V., Vol. 64, pp. 169–187.

Freedman, S. and Jin, G.Z. (2011), *Learning by Doing with Asymmetric Information: Evidence from Prosper.com*, No. 16855, *NBER Working Paper*, available at:https://doi.org/10.3386/w16855.

Freedman, S. and Jin, G.Z. (2017), "The information value of online social networks: Lessons from peer-to-peer lending", *International Journal of Industrial Organization*, Elsevier B.V., Vol. 51, pp. 185–222.

Gonzalez, L. and Loureiro, Y.K. (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*, Elsevier B.V., Vol. 2, pp. 44–58.

Greiner, M.E. and Wang, H. (2010), "Building Consumer-to-Consumer Trust in E-Finance Marketplaces: An Empirical Analysis", *International Journal of Electronic Commerce,* Vol. 15 No. 2, pp. 105–136.

Han, J.T., Chen, Q., Liu, J.G., Luo, X.L. and Fan, W. (2018), "The persuasion of borrowers' voluntary information in peer to peer lending: An empirical study based on elaboration likelihood model", *Computers in Human Behavior*, Elsevier Ltd, Vol. 78, pp. 200–214.

Herzenstein, M., Dholakia, U.M. and Andrews, R.L. (2011), "Strategic Herding Behavior in Peer-to-Peer Loan Auctions", *Journal of Interactive Marketing*, Direct Marketing Educational Foundation, Inc., Vol. 25 No. 1, pp. 27–36.

Iyer, R., Khwaja, A.I., Luttmer, E.F.P. and Shue, K. (2015), "Screening Peers Softly: Inferring the Quality of Small Borrowers", *Management Science*, Vol. 62 No. 6, pp. 1554–1577.

Jin, J., Fan, B., Dai, S. and Ma, Q. (2017), "Beauty premium: Event-related potentials evidence of how physical attractiveness matters in online peer-to-peer lending", *Neuroscience Letters*, Elsevier Ireland Ltd, Vol. 640, pp. 130–135.

Jin, J., Shang, Q. and Ma, Q. (2019), "The role of appearance attractiveness and loan amount in peer-to-peer lending: Evidence from event-related potentials", *Neuroscience Letters*, Elsevier, Vol. 692 No. October 2018, pp. 10–15.

Karlan, D.S. (2007), "Social connections and group banking", *Economic Journal*, Vol. 117 No. 517, pp. 52–84.

Karsidi, R., Trinugroho, I., Nugroho, L.I. and Prabowo, A. (2015), "Why households borrow from informal predatory lenders: Evidence from Indonesia", *Journal of Economics and Economic Education Research*, Vol. 16 No. 2, pp. 173–181.

Lee, E. and Lee, B. (2012), "Herding behavior in online P2P lending: An empirical investigation", *Electronic Commerce Research and Applications*, Elsevier B.V., Vol. 11 No. 5, pp. 495–503.

Milne, A. and Parboteeah, P. (2016), "The Business Models and Economics of Peer-to-Peer Lending", *European Credit Research Institute (ECRI)*, No. May, pp. 1–37.

Pope, D.G. and Sydnor, J.R. (2011), "What's in a Picture? Evidence of Discrimination from Prosper.com", *The Journal of Human Resources*, Vol. 46 No. 1, pp. 53–92.

Prystav, F. (2016), "Personal information in peer-to-peer loan applications: Is less more?", *Journal of Behavioral and Experimental Finance*, Elsevier B.V., Vol. 9, pp. 6–19.

de Roure, C., Pelizzon, L. and Tasca, P. (2016), "How Does P2P Lending Fit into the Consumer Credit Market?", *SSRN Electronic Journal*, pp. 1–35.

Serrano-Cinca, C., Gutiérrez-Nieto, B. and López-Palacios, L. (2015), "Determinants of default in P2P lending", *PLoS ONE*, Vol. 10 No. 10, pp. 1–22.

Trinugroho, I., Agusman, A., Ariefiento, M.D., Darsono, D. and Tarazi, A. (2015), "Determinants of cross regional disparity in financial deepening Evidence from Indonesian provinces", *Economics Bulletin*, Vol. 35 No. 2, pp. 896–910.

Wang, Z., Jiang, C., Ding, Y., Lyu, X. and Liu, Y. (2018), “A Novel behavioral scoring model for estimating probability of default over time in peer-to-peer lending”, *Electronic Commerce Research and Applications*, Elsevier B.V., Vol. 27, pp. 74–82.

Xia, Y., Liu, C. and Liu, N. (2017), “Cost-sensitive boosted tree for loan evaluation in peer-to-peer lending”, *Electronic Commerce Research and Applications*, Elsevier B.V., Vol. 24, pp. 30–49.

Table 1. Descriptive statistics

This table describes the descriptive statistics of our sample. Our sample consists data from three P2P lending platforms in Indonesia namely Alpha, Beta, and Gamma (not the real name)

	Platform = Alpha					Platform = Beta					Platform = Gamma				
Variable	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
default	1,039,555	0.003	0.050	0	1	6,951	0.052	0.221	0	1	168,434	0.116	0.320	0	1
loan_rate	1,039,555	0.288	0.003	0.192	0.384	6,951	0.200	0.056	0.14	0.3	168,434	2.729	0.720	0.14	3.65
reg_pojk77	1,039,555	0.835	0.371	0	1	6,951	0.941	0.235	0	1	168,434	0.916	0.278	0	1
amount	1,039,555	3.096	1.166	0.5	13	6,951	60.431	79.892	2	600	168,434	2.914	1.928	1	8
period	1,039,555	342.055	36.441	70	350	6,951	349.193	41.146	90	360	168,434	40.828	26.503	10	90
woman	1,039,555	1	0	1	1	6,951	0.461	0.498	0	1	168,434	0.464	0.499	0	1
married	1,039,555	0.996	0.061	0	1	6,951	0.711	0.453	0	1	168,434	0.647	0.478	0	1
house						6,951	0.705	0.456	0	1	168,434	0.261	0.439	0	1
education						6,917	4.639	0.811	3	6	168,434	4.267	1.738	1	7
income	1,039,555	3.101	1.920	0.9	9	6,951	19.664	20.620	2.2	80	168,434	5.970	3.517	2.5	24
age	1,039,555	41.564	9.400	22	60	6,951	37.043	8.065	22	60	168,434	26.314	8.996	14	60

Note: *Default_status* is a dummy variable equals to 1 if the loan is default. *Loan_rate* is yearly loan rate. *Amount* is the amount of loan in million IDR. *Period* is the period of the loan (number of days). *Woman* is a dummy variable equals to 1 if woman. *Married* is a dummy variable equals 1 if married. *House* equals to 1 if the borrower owns a house. *Educations* is formal degree of education of borrower, ranges from 1 to 7 (1=Kindergarten; 2=Elementary School; 3=Junior High School; 4=Senior High School; 5=Undergraduate Degree; 6=Master Degree; 7=Doctoral Degree). *Income* is monthly borrower's income in million IDR. *Age* is the borrower's age.

Table 2. Loan rate and borrower characteristics

	Alpha	Beta	Gamma
	(1)	(2)	(3)
log_amount	-0.00178***	-0.000809	-0.444***
	(-58.45)	(-1.64)	(-147.28)
log_period	0.00280***	-0.0128***	-0.455***
	(59.70)	(-3.91)	(-143.06)
married	-0.000205***	-0.0169***	0.00836***
	(-12.48)	(-13.88)	(2.74)
log_income	-0.00000718	-0.0227***	-0.00897***
	(-1.26)	(-31.12)	(-2.93)
log_age	-0.0000961***	0.0210***	-0.0408***
	(-7.16)	(7.51)	(-9.16)
woman		0.00477***	-0.00377
		(4.15)	(-1.50)
house		-0.0211***	0.00365
		(-17.47)	(1.23)
education		-0.0143***	0.00180**
		(-18.78)	(2.34)
constant	0.300***	0.694***	11.00***
	(1378.39)	(33.19)	(181.97)
N	1039555	6917	168434
R-sq.	0.0388	0.392	0.501

Note: The dependent variable is the yearly rate of loan in P2P lending. Variable *woman* in Alpha is dropped from the analysis because all of the borrowers is woman (woman=1, man=0). Variable *house* and *education* are not available from Alpha. Robust t-statistics are in parentheses. ***, **, and * denotes significance in 1%, 5%, and 10% levels respectively.

Table 3. Loan default and borrower characteristics

	Alpha	Beta	Gamma
	(1)	(2)	(3)
loan_rate	31.93***	-0.866	1.239***
	(26.56)	(-0.83)	(37.56)
log_amount	1.370***	0.486***	0.316***
	(23.27)	(9.08)	(13.64)
log_period	-1.310***	2.081*	1.823***
	(-6.62)	(1.86)	(52.14)
married	0.771*	-0.422***	0.000920
	(1.72)	(-3.07)	(0.05)
log_income	-1.016***	0.562***	0.0295
	(-29.27)	(6.15)	(1.50)
log_age	0.293***	-0.455	-0.215***
	(3.47)	(-1.29)	(-7.93)
gender		2.620***	0.0479***
		(11.87)	(3.01)
house		-0.204*	0.0369*
		(-1.80)	(1.94)
education		-0.213**	-0.0150***
		(-2.07)	(-3.03)
constant	-14.65***	-32.61***	-17.49***
	(-9.91)	(-4.88)	(-31.81)
N	1022780	6509	168434

Note: The dependent variable is loan default (1=default; 0=not default). Variable *woman* in Alpha is dropped from the analysis because all of the borrowers is woman (woman=1, man=0). Variable *house* and *education* are not available from Alpha. Robust t-statistics are in parentheses. ***, **, and * denotes significance in 1%, 5%, and 10% levels respectively.

Table 4. Loan rate, regulation, and borrower characteristics

	Alpha	Beta	Gamma
	(1)	(2)	(3)
reg_pojk77	0.0348***	-0.128***	3.278***
	(45.00)	(-3.38)	(12.48)
log_amount	-0.000242***	-0.00659***	-0.240***
	(-13.03)	(-3.06)	(-13.61)
*reg_pojk77*log_amount*	-0.00250***	0.00607***	-0.215***
	(-48.58)	(2.80)	(-12.06)
log_period	0.00442***	-0.0118***	-0.448***
	(58.63)	(-3.52)	(-140.05)
married	-0.000171***	-0.0169***	0.00838***
	(-9.70)	(-13.90)	(2.75)
log_income	-0.0000387***	-0.0226***	-0.00896***
	(-6.68)	(-30.71)	(-2.93)
log_age	-0.000119***	0.0204***	-0.0411***
	(-8.84)	(7.26)	(-9.23)
gender		0.00461***	-0.00395
		(4.00)	(-1.57)
house		-0.0209***	0.00365
		(-17.18)	(1.23)
education		-0.0144***	0.00180**
		(-18.88)	(2.34)
constant	0.269***	0.789***	7.986***
	(526.49)	(20.63)	(30.23)
N	1039555	6917	168434
R-sq.	0.0491	0.393	0.501

Notes: The dependent variable is the yearly rate of loan in P2P lending. Variable *woman* in Alpha is dropped from the analysis because all of the borrowers is woman (woman=1, man=0). Variable *house* and *education* are not available from Alpha. Robust t-statistics are in parentheses. ***, **, and * denotes significance in 1%, 5%, and 10% levels respectively.

Table 5. Loan default, regulation, and borrower characteristics

	Alpha	Beta	Gamma
	(1)	(2)	(3)
loan_rate	-117.4***	-142.3***	1.007***
	(-2.89)	(-6.11)	(5.69)
reg_pojk77	-41.75***	-23.68***	0.534
	(-3.56)	(-6.31)	(0.95)
*loan_rate*reg_pojk77*	151.7***	143.9***	0.244
	(3.73)	(6.18)	(1.35)
log_amount	1.369***	0.512***	0.319***
	(23.28)	(9.52)	(13.79)
log_period	-1.308***	2.263**	1.834***
	(-6.61)	(2.05)	(51.26)
married	0.771*	-0.334**	0.000942
	(1.72)	(-2.44)	(0.05)
log_income	-1.017***	0.655***	0.0294
	(-29.28)	(6.85)	(1.50)
log_age	0.294***	-0.498	-0.214***
	(3.49)	(-1.45)	(-7.90)
gender		2.394***	0.0479***
		(12.31)	(3.01)
house		-0.185*	0.0367*
		(-1.65)	(1.93)
education		-0.107	-0.0150***
		(-1.00)	(-3.03)
constant	26.41**	-12.61***	-16.86***
	(2.24)	(-3.30)	(-22.69)
N	1022780	6917	168434

Notes: The dependent variable is loan default (1=default; 0=not default). Variable *woman* in Alpha is dropped from the analysis because all of the borrowers is woman (woman=1, man=0). Variable *house* and *education* are not available from Alpha. Robust t-statistics are in parentheses. ***, **, and * denotes significance in 1%, 5%, and 10% levels respectively.