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Determinants of default in the bitcoin lending market

The case of Bitbond platform

by

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ABSTRACT
This paper studies the bitcoin lending market and the factors explaining loans defaults. No financial intermediation implies that investors are faced directly with the credit risk. This increases information asymmetry at the cost of the lenders, so bitcoin lending platforms try to reduce this negative effect by providing information about the borrowers and their loan requests. Credit grade and interest rate are assigned by the platform, which are the main variables of the interest. This study has been conducted on the largest active bitcoin lending platform Bitbond covering 2013-2017 period with overall (N=1449) loans outstanding. Correlation analysis and univariate means tests have been used to analyse the data, while logistic regressions have been used for predicting default. Factors explaining default are loan amount, loan term and purpose of working capital, as well as industry of education and transportation and the total number of identifications. The interest rate assigned is the most predictive factor of the default followed by the grade, though other additional variables still improve the accuracy of the models. This paper contributes to the current literature since it is the first, to the best of our knowledge, analysing the bitcoin lending market.

Key words: bitcoin, peer-to-peer lending, bitcoin lending, default, credit grade, interest rate, financial intermediation.

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1. INTRODUCTION

Online peer-to-peer (p2p) bitcoin lending has recently[1] emerged as a new form of loan initiation for the credit market, though this particular market lacks any empirical investigation, especially credit risk estimation (i.e., probability of default). Bitcoin lending could be defined as lending in bitcoins[2] (BTC) through specialized websites that bring together suitable individual lenders and borrowers. In academic literature emergence of alternative financing industry[3], including bitcoin lending is mainly explained as a reduction in credit-rationing problem[4] or as a financing innovation due to crisis repercussions[5] (Stiglitz & Weiss, 1981; Meteescu, 2015). This sector has been growing exponentially (Appendix A) and is predicted to reach 897.85 billion dollars by 2024 (The Transparency Market Research, 2016). By taking larger part of lending sector's market share, the growth of p2p lending leads to the broad and long-term structural change within finance industry (Zhang, Ziegler, Burton, Garvey, Wardrop, Lui & James, 2016). Serving the non "bankable" borrowers[6] represents a huge opportunity for investors (i.e. lenders) with increasing access to around 2 billion people who cannot use formal financial services (World Bank, 2017). In addition to that, lenders are willing to invest in p2p markets to get rid of the "middle-man"[7] by reducing transaction costs, which leads to higher return of investment rate (ROI) (Klafft, 2008). Moreover, transparency and "feeling of fairness"[8] involved in the market have an additional stimulus (Klafft, 2008).

Exploring new investment possibilities investors prefer to invest in Bitcoin Lending market as an alternative to p2p lending. Mateecsu (2015) disclose that p2p markets are based domestically. Global diversity of portfolio achieved through bitcoin lowers pro-cyclical credit risk as well as gives reachability to international borrowers, who are willing to pay more than borrowers from U.S. or other developed countries (Appendix A). Lustman (2015) reports 1.77% ROI from bitcoin loans, while p2p alternative ROI is 1.11% for Prosper and 1.08% for Lending club platforms. Furthermore, most of p2p lending platforms' cooperation with banks increases lenders' and borrowers' fees, while Bitcoin lending works independent and can offer 0% fees

[1] First platform established in 2013.
[2] A type of a digital currency produced by a public network rather than any government (Dictionary of Cambridge).
[3] The one outside the traditional financing alternatives, for example, crowdfunding or peer-to-peer lending (Zhang et al. (2016).
[4] Exclusion of low credit rating/ small amount loans borrowers, even if a high interest rates are agreed to be paid (Stiglitz & Weiss, 1981).
[5] In 2008-2015, $235 billion was paid in fines by the top 20 banks, which increased mistrust in traditional banking system (Bajpai, 2016).
[6] A Segment of borrowers that banks are unwilling to supply (Roure, Pelizzon & Tasca, 2016).
[7] A person who arranges business or political deals between other people (Oxford Dictionary).
[8] Trust in p2p markets as the information of all transactions is accessible by anyone (Klafft, 2008).

for the lenders. Furthermore, Carrick (2016) findings show that bitcoin could be used as a hedge due to significant negative correlation with the major currencies, while its characteristics make it well-suited to work as a complement to emerging market currencies and that there are ways to minimize bitcoin's risks. "Bitcoin is better than currency in that you do not have to be physically in the same place and, of course, for large transactions, currency can get pretty inconvenient – Bill Gates" (Shandrow, 2014).

Serrano-Cinca, Gutiérrez-Nieto & López-Palacios (2015) highlight that information asymmetry is a fundamental issue within any peer-to-peer based platform. While information asymmetry is reduced through traditional financial intermediaries[9] (Diamond, 1984), p2p lending seems to struggle by allocating credit efficiently as investors lack expertise to evaluate borrowers' creditworthiness by themselves (Mild, Waitz & Wöckl, 2015; Emerker et al., 2015; Klafft, 2008). Stiglitz and Weiss (1981) inform that information asymmetry problems may cause market breakdowns. Therefore, any online p2p lending platform (including Bitcoin lending) is subjected to mitigate information asymmetry in order to reach long-term success (Dong, 2017). Some researchers suggest information asymmetry can be reduced through evaluating only borrower's hard information[10] (Li, 2016; Polena & Regner, 2016; Serrano-Cinca et al., 2015), while others suggest that adding soft information[11] helps to reduce it even more (e.g. Herzenstein and Andrews, 2008; Iyer et al., 2009; Dorfleitner et al., 2016; Chen et al., 2009).

Hence, the main aim of this paper is to investigate the determinants of default probability, confirm if lenders' decisions are purely based on nominal interest rates (as directly related to ROI), or any additional information can lower information asymmetry. The empirical study uses the data from Bitbond platform, the largest active Germany based bitcoin-lending platform. Hypotheses have been tested by determining significant differences in independent variables by using cross-tabulations (Chi-squared test) and independent t-test between defaulted and fully paid loans. Moreover, logistic regressions have been conducted to define the significant relationships between categorical dependent variable (defaulted or not) and groups of independent explanatory variables such as borrowers' assessment, loans' characteristics, additional borrowers' characteristics and borrowers' indebtedness. An additional hypothesis is investigated to see if alternative creditworthiness approach (based on Big Data) can perfectly

[9] Banks, insurance companies, credit unions and etc.
[10] Borrowers' credit information as FICO and financial situation as debt-to-income ratio (Dong, 2017).
[11] Personal characteristics as social networks, photographs and descriptive text of borrower's profile (Dong, 2017).

identify borrowers' probability of default in Bitbond platform, as well as if bitcoin volatility[12] could have an explanatory power of default rates. It is expected to find that any additional information provided, except borrowers' characteristics as they should already be accounted in the credit grade assigned by the Bitbond, would lower information asymmetry in lenders' decision-making. Moreover, supplementary assumption is made that structural nominal interest rate change in 28/09/2015 has an effect on default determinants. For this reason, additional analysis of two subsample periods, before and after nominal interest rate increase has been set.

Analysis showed high correlation (~0.9) between nominal interest rate and grade, causing large mutual predictability of each other, thus independent variables were examined separately. Logistic regression models (1-5) are based on full sample with grade and loan term as the key borrower's assessment variables, while models (6-9) are based on subsamples (before and after interest rate change) with nominal interest rate and loan term as the key variables. We found that additional information helps to reduce information asymmetry. In full sample model independent variables such as loan amount, loan term and purpose of working capital, as well as industry of education and transportation and the total number of identification are significant determinants of default rates. Subsample analysis shows that interest rate has no higher explanatory power than a grade and any of them should be used as a determinant.

By investigating a new form of alternative financing (bitcoin lending), its reasons for default and differences with p2p lending, this thesis greatly contributes in filling the gap in the current literature. Our findings to some extent also shed the light on the effectiveness of using Big Data information as an alternative credit worthiness scoring in online lending market. Furthermore, this thesis includes the analysis of how interest rate change affects default rates, which have not been covered on any p2p previous studies, since they have not experienced this issue before.

The structure of the paper is organized as follows: Section 2 presents a related literature review and theoretical background on bitcoin and p2p lending markets; Section 3 describes institutional background; Section 4 explains selected data and methodology. Section 5 presents the main research and the empirical results. Finally, Section 6 consists of conclusions and suggested further research.

[12] Borrowers' option of the base currency, either fixed USD/BTC exchange rate or bitcoins.

2. LITERATURE REVIEW

2.1. WHY FINANCIAL INTERMEDIARIES (BANKS) EXIST

To understand how bitcoin lending fits into financial sector, the reasons behind financial intermediaries' existence are important to investigate. Lending and borrowing money for the first time encountered in the Mesopotamian society (Graeber, 2011). Matching the supply and demand is significantly more important in the present day, as many forms of trading capital has evolved. To serve this purpose various financial intermediaries exist. The most common way to save, invest or raise capital is through banks as the trust associated with a governments' protection and professional expertise creates an idea of financial stability. Casu, Girardone & Molyneux (2006) define three transformation functions for matching supply of short-term deposits with demand of long-term loans. Firstly, size transformation is applied using economy of scale[13] to match large borrowers' capital request. Secondly, maturity transformation is applied through a process like securitization to solve liquidity risk from a mismatch of short-term inflows and long-term outflows. Finally, risk transformation helps to reduce default risk by diversifying client's investments, screening and monitoring information as well as keeping capital reserves. These three functions are related to the core principles of the banks' existence.

Casu, et al. (2006) define the most fundamental five theories explaining banks existence – delegated monitoring, information production, liquidity transformation, consumption smoothing and commitment mechanism discussed in the academic literature. The main theory - delegated monitoring - is argued by Diamond (1984) as a necessary information asymmetry solution. Diamond (1984) explains how third party involvement reduces free rider and adverse selection[14] problems. Banks provide a solution through expertise in monitoring borrowers and evaluating their credit worthiness effectively. Secondly, information production is a costly process without financial intermediaries. For example, finding possible investment opportunities for lenders would incur substantial search costs due to duplication of information and time, while through banks information economy of scale is accessible (Casu et al., 2006). Thirdly, authors also define the liquidity transformation as the superior liquidity feature using

[13] Large number of depositors.

[14] Assuming direct interaction between borrower and lender, the lender suffers from adverse selection, as only the borrower knows the actual probability of loan repayment. The free rider problem emerges as a market failure, when more than one lender would fund borrower, since processing/monitoring information is assumed to be a collective good, but neither of the lenders actually do, as it is costly and wasteful if done separately.

banks' deposits comparing to what liquidity level is accessible through alternatives such as stocks or bonds. Forth, Bhattacharya & Thakor (1993) define consumption smoothing as insurance against shocks to consumption. Assuming that the economic agent has uncertain preferences driving the demand of assets with high liquidity, financial intermediaries provide stability of consumption. Debtors' liquidity shocks are assisted by finding lenders in a short time frame using cumulative information about them through banks' economy of scale. Finally, the recently developed theory of commitment mechanism tries to find out why illiquid long-term loans are financed by demand deposits. This mechanism is explained as a discipline device for the banking system, as it directly affects the balance sheet and ensures banks hold sufficient capital resources (Casu et al., 2006). To sum up, banks exist as matchmakers of supply and demand for financial assets by reducing substantial physical, information and coordination costs both for lenders and borrowers (Earl & Dow, 1982).

2.2. Borrowing in foreign currency and the case of bitcoin

Bitcoin borrowing and lending can be treated as businesses' trade activity in foreign currency since individual investors lend bitcoins internationally for their business purposes. Currency in general is a system of money for the common use with three characteristics described as follows: (1) medium of exchange – means of payment, (2) unit of account – measure of value, and (3) value storage – transferring purchasing power from the present into the future (Krugman, Obstfeld & Melitz, 2012).

Firms in emerging markets often borrow in a foreign rather than the domestic currency (Brown, Kirschenmann & Ongena, 2010). Beckmann & Stix (2015) state that foreign currency loans are widespread in many parts of the world with a share of about 25% in Latin America, 40% in the Middle East and more than 50% in several Central and Eastern European countries. Keloharju & Niskanen (2001) indicate three reasons why companies might want to raise capital in foreign currencies: a) it hedges against foreign exchange exposures; b) it might be cheaper than to borrow in domestic currency; and c) foreign debt might be more attractive than domestic due to speculation.

To begin with, hedging is important for most corporations in order to avoid exchange risk exposures. Cowan (2006) model foresees that there is more foreign debt in countries with higher foreign income. In addition, there is more foreign debt for firms in countries, which have higher interest rate differences and lower exchange risk (Brown et al., 2010). There is, however, less incentive to take foreign currency loans when the exchange rate is more volatile due to the higher default risk on unhedged loans as mentioned in Brown et al., 2010. He & Ng (1998) studied Japanese multinational corporations' value and found that depreciation (appreciation) of the yen against other foreign currencies has a positive (adverse) impact on stock returns. Pantzalis, Simkins & Laux (2001) investigated U.S. multinational corporations and found that while domestic firms have to rely fully on financial instruments to hedge their exchange risk exposure, multinationals benefit from foreign currency borrowing as operation flexibility from their foreign network works like an additional hedging tool. Secondly, Brzezina, Chmielewski & Niedźwiedzińska (2010) studied the Czech Republic, Hungary, Poland and Slovakia private markets and found that all of these countries have a substantial share of foreign currency loans due to higher borrowing costs in domestic currency. Keloharju & Niskanen (2001) discuss that issuing loans in the Euromarkets may be more economical than domestic borrowing since it helps to bypass withholding taxes and capital controls imposed by many governments. Finally, Keloharju & Niskanen (2001) found that a financial manager might choose to deviate from a hedging strategy if he believes that after adjusting for the risk the difference in interest rates between two currencies mismatch the expected exchange rate change. This belief is consistent with overconfidence, though authors also indicate, that managers might be motivated by the failure of International Fisher's Effect[15], thus creating speculative incentives.

Another argument by Beckmann & Stix (2015) state that foreign debt might actually be less risky than a local currency loan in an environment of high and volatile inflation. Thus, they also argue that unstable and unpredictable monetary policy constitutes a key driver of foreign currency borrowing. Furthermore, currency denomination of loans depends not only on the firms' preferred currency, but also on the loans that banks can offer to them and banks' overall access to the foreign currency market (Brown et al., 2010).

To sum up, there is growing importance in foreign currency borrowing, especially in emerging markets. Therefore, it is essential to understand if bitcoin borrowing is attractive as a foreign currency investment. The academic literature analyses if bitcoin (virtual currency[16]) can be treated as a real currency. One part of the literature argues that bitcoin does not behave as a real

[15] Differences in nominal interest rates reflect expected changes in the spot exchange rate between countries.

[16] Digital representation of value that is neither issued by a central bank or a public authority, nor even attached to a flat currency. It is also accepted by persons as a means of payment and can be transferred, stored or traded electronically (ECB, 2016).

currency, because of not fulfilling money requirements, but is more a speculative tool for investments (Velde 2013; Yermack 2014). Another part argues that bitcoin has a potential to be treated as a global currency (Plassaras 2013; Satran 2013; Luther & White 2014; Folkinshteyn, Lennon & Reilly 2015). Carrick (2016) however found, that bitcoin has characteristics that make it well-suited to work as a complement to emerging market currencies. The author discovers significant negative correlation with the major currencies indicating that bitcoin can be used as a hedge of risk and also less significant negative correlation with emerging market currencies concluding that it can be as a complement. Therefore, bitcoin suits well as a foreign currency investment due to its applicability as a hedge against foreign currencies and to emerging markets. Moreover, it also suits well as a hedging tool if companies have their part of income in bitcoins. For example, variety of companies accept bitcoin for their products or services, which gives an incentive to borrow or lend bitcoins and at the same time hedge against foreign risk exposures. Thus, companies might want to raise capital in bitcoins as a hedge against foreign exchange exposures already mentioned before by Keloharju & Niskanen (2001).

Following other Keloharju & Niskanen (2001) arguments, Wonglimpiyarat (2016) emphasizes, that many countries are still reluctant to accept bitcoin, as it is not backed by any government and is vulnerable to manipulations or speculations. The author gives examples that in China, banks have blocked financial institutions from handling bitcoin transactions and restricted their transfers; in Thailand the bank does not authorize bitcoin to operate, while in South Korea there are no laws regulating bitcoin. Therefore, it suits as foreign currency investment due to weak regulations and the cost advantage, as there are no taxes or capital requirements involved. Finally, since it is a rather new currency and has no underlying intrinsic value derived from consumption or production (like any other commodity such as gold), risk and uncertainty about the whole system arises, encouraging possible speculative movements. Bitcoin is also more exposed to cyber-attacks than any regular currency - Moore and Christin (2013) have analysed 40 bitcoin exchanges and found out that 18 were closed due to hackers or other criminal activity.

However, despite that bitcoin seems suitable as a foreign currency investment, it is important to take into account bitcoin's price volatility [17] compared with regular currencies and commodities (see Appendix A). Kancs, Ciaian & Rajcaniova (2015) state that the existing

[17] For example, the price on March 24th, 2017 per bitcoin was US$990, while just one week before, bitcoin's price was coasting along at $1,215-1,235 per BTC (Redman, 2017).

studies in the literature suggest three types of drivers determining bitcoin price formation: (i) market forces of bitcoin supply and demand, (ii) bitcoin attractiveness, and (iii) global macroeconomic and financial developments. Bitcoin supply is the total amount of bitcoins in the market and demand is its use for exchange and velocity[18]. The quantity theory of money and Fisher's equation (MV = PT) imply that the price of bitcoin decreases with the velocity (V) and the amount of bitcoins in the market (M-money supply), but increases with the overall transactions of goods and services (T) and general price level (P). Bitcoin price fluctuates mainly due to the demand since supply is fixed in the long run. According to Luther & White (2014), any change in the expectation that bitcoin will be used to make payments in the future will affect the willingness of individuals to hold bitcoin today. Various shocks to the demand and attractiveness, such as trust and acceptance in the market, are causing bitcoin price to fluctuate – i.e. increasing number of acceptance by major online retailers either in a direct or indirect way (Paypal, Amazon, Microsoft), food companies (Subway, WholeFoods), travel agencies (WebJet, LOT Polish Airlines) and many more lowers the price. Kancs et al. (2015) state, on the other hand, that bitcoin price may be affected by its attractiveness as an investment opportunity for potential investors. Lee (2014) found that positive press attracts new users, thus price increases as press coverage increases, while bad news pushes users to sell bitcoins and price decreases even more. Furthermore, the expectation of bitcoin price is also determined by global macroeconomics and financial developments. These indicators consist of macroeconomic measures such as GDP per capita, unemployment, Consumer Confidence Index, also financial indicators, such as oil price, stock exchanges and exchange rates. Nevertheless, according to Kancs et al. (2015), since its introduction in 2009, bitcoin has been described by a remarkable increase in the number of transactions and market capitalization. According to realtimebitcoin.info (2017), bitcoin volume surpassed 17 billion US dollars in March 2017. By comparison, in 2015, it had a volume of 5 billion US dollars. If looking at its market capitalization's rapid growth since 2009, from a mere idea to a legitimate currency by mid-2014, circulation of about $17 billion of bitcoins was reached as of March 28, 2017 (Appendix A).

Overall, bitcoin can be treated as an alternative foreign currency investment. Moore & Christin (2013) state that Bitcoin's key comparative advantages over existing currencies lie in its entirely decentralized nature and in the use of proof-of-work mechanisms to constrain the money supply. Bitcoin also benefited from strongly negative reactions against the banking system,

[18] Measures the frequency indicating when one bitcoin is used to purchase any good or service.

following the 2008 financial crisis. Similar in spirit to hard commodities such as gold, Bitcoin offers an alternative to those who fear that quantitative easing[19] policies might trigger runaway inflation. Lastly, as Ou (2017) indicates, even China cannot kill bitcoin - people are using virtual private networks to access bitcoin and plenty of trading happens on lesser-known sites and on micro-messaging services. Thus, despite strict government regulations, China remains one of the biggest bitcoin users.

2.3. How alternative financing market fits within traditional banking system?

It is important to see how well the alternative financing industry fits within traditional banking system mentioned in part 2.1, as this would indicate if alternative market has an actual chance to overtake the current financial system. While there is a broad consensus on the importance of banks in financial intermediation, the recent banking crisis has highlighted shortcomings in the traditional lending models, particularly in allocating credit to smaller borrowers (Weiss, Pelger & Horsch, 2010). Blaseg and Koetter (2015) explain peer-to-peer emergence as a response to the challenges of rising external financing after the financial crisis of 2008. Meteescu (2015) adds that the financial crisis shattered public confidence within the traditional intermediaries of the financial system (banks), when millions of borrowers had to bear an extraordinary debt burden and an almost total cut off from new sources of credit. This created the ambition to cut out the intermediary and create space for internet-based platforms. Furthermore, the World Bank Global Financial Development Database (2017) indicates the difference between low-high income countries and their accessibility to financing. On average 30% of higher-middle to low-middle income countries reported challenges for financing during 2002-2014 period, while in low-income countries it reached 60% in 2010. This shows that the consumption smoothing theory discussed part in 2.1 is not fully solved by the traditional banking system – credit rationing problem exists. Serrano-Cinca et al. (2015) highlight that this phenomenon has increased during the economic downturn. Koch (1997) explains this by Pareto's 80/20[20] distribution, as financial intermediaries tend to select clients and distinguish them as profitable

[19] The introduction of new money into the money supply by a central bank (Oxford Dictionary).
[20] The fat tail in 80/20 distribution curve represents best clients' loans, as they are served by the private banking sector as profitable, while the not servable part includes small loans in the long and thin tail due to low profitability and fixed costs.

or not for their industry. Hales (1995) finding shows that less than 10% of bank clients generate 90% of its profits.

A comparison of loans' interest rates and risk level between the traditional banking sector and the main peer-to-peer platform in Germany (i.e. Auxmoney) led to the conclusion that the peer-to-peer platform "is serving borrowers largely considered not "bankable" by banks" (Roure, Pelizzon & Tasca, 2016). This neglected segment of the consumer credit market is characterized by high risk and small credit lines (Roure et al., 2016). According to the authors, the main reasons for the banks' inability to serve this market are: exposure to higher default rates may lead them to fees and higher capital requirements; marginal cost differences between mortar-and-brick and the internet based system, thus small credit loan process can be costlier than profitable; bank's lending procedures are paper intensive and complex. Blaseg & Koetter (2015) highlight that ventures or small business are more likely to use alternative investment sources when their bank is affected by a credit crunch, thus alternative approach is useful as "critical source of capital in stressful times for banks".

The hypothetical scenario of perfect screening and monitoring by banks (Diamond, 1984) is proven to be incorrect to some extent, as no new business models competing with the banking sector would emerge. Chen et al. (2013) emphasise information asymmetry problems within the small business and potential credit (including banks). Authors also highlight that small firms tend to have insufficient tangible assets for collateral, as well as transparency issue with financial statements. They describe that the information asymmetry problem can be solved by assigning attentive soft information evaluation. Moreover, Serrano-Cinca et al. (2015) specify reasons why financial institutions have higher transaction costs compared with online based alternatives. For banks it is costly to monitor loan repayments, to pay Federal Deposit Insurance Corporation fee for staying within capital requirements, to pay the other manual processing costs as well as to experience financial friction from matching short-term inflows (i.e. deposits) and long-term outflows (i.e. loans). This leads to situation, where banks only perform soft information checks on profitable or long-relationship clients (Chen et al., 2013). Therefore, the unserved not "bankable" clients' market share leaves space for an alternative financing platform accessible by everyone, even if most of the risk is bared by individual investors (no commitment mechanism (see 2.1)) or is not as liquid as deposits within traditional banks (lower liquidity transformation).

2.4. LENDERS RISK

Every investment carries some degree of risk while risk management deals with this issue. There is a possibility for investors or portfolio managers to increase or decrease their risk depending of their own goals (Baker & Filbeck, 2015). The authors, however, indicate that managing risk has become rather difficult due to the multiple aspects of risk. Bender & Nielsen (2009) state that risk management should be in line with the investment objectives and time framework, not just limited to a specific single risk measure. Baker & Filbeck (2015) describe the main types of risk as follows: a) market risk - arises due to the overall performance of financial markets and cannot be diversified away, i.e., natural disasters or recessions; b) specific risk - related directly to the particular security (i.e., company declares bankruptcy, so its stock price is affected negatively); c) downside risk - associated with non-linear portfolio strategies or value-at-risk measure commonly used by banks and portfolio management; c) credit risk – probability of default by the counterparty; d) operational risk - loss due to inadequate monitoring systems, management failure or human errors; and e) liquidity risk - inability to sufficiently liquidate a position at a fair price.

In peer-to-peer lending excluding the middleman makes individual lenders responsible to account for cost factors like default risk while agreeing with the interest rates. Mild et al. (2015) explain that inaccurate assessment of credit risk in an aggregate level is a threat to financial sector, for example, 1929 financial crisis or 2008 subprime crisis. Therefore, probability of default, an aspect of the overarching concept of credit risk is a key factor for lenders, both individually and collectively in peer-to-peer based markets.

2.4.1 PROBABILITY OF DEFAULT

In order to account for the credit risk, the concept of probability of default (PD)[21] and alternative credit scoring techniques are presented in details. Under Basel II regulation PD is also a part of the capital requirement calculation for the banking industry, thus PD is widely used in risk management, credit analysis and finance.

[21] Probability of default (PD) is the likelihood of default in a specified time period, usually one year. It provides an estimate of how likely the customer will be to not meet their obligations to pay in time and in full (Basel Committee, 2005)

In a lending market a credit score is a measure representing how creditworthy the consumer is – it describes how borrower's characteristics imply default. Grannis (2015) showed that commercial and industrial loans outstanding in the U.S. have grown rapidly from worth around 0,95$ trillions in 1999 to almost 2$ trillions in 2015. This increased trend of borrowing allied with greater competition and the emergence of new computer technology have led to the development of sophisticated statistical models to aid the credit granting decisions – credit scoring (Hand & Henley, 2015). Li, Shang & Su (2014) empirical research suggests that a borrower's past financial credit score is a reasonably good indicator for the ex-post loan performance. The most well known credit score FICO was developed by Fair Isaac Corporation in the U.S. in 1989 and it is based on consumer credit files. Customer's data is grouped into 5 categories with a percentage indicating each category's relevance for the credit score: 35% for payment history, 30% for amounts owed, 15% for length of credit history, 10% for new credit and 10% for credit mix, but FICO[22] score's exact formula is unfortunately held secretly (Polena & Regner, 2016). P2p and Bitcoin lending sites sometimes rely on this third party information as an additional tool in order to assign a grade to the borrower. Moreover, Smith, Staten, Eyssell, Karig, Freeborn & Golden (2013) findings argue that credit-bureau data are accurate enough for efficient lending by financial institutions and management of accounts by creditors.

Other things, which can influence probability of default, are macroeconomic variables such as GDP growth rates, price index or unemployment rate. These variables affect all borrowers, so defaults are correlated. As Hull (2015) indicates, if credit correlation increases (as it tends to do in stressed economic conditions), the risk for a financial institution with a portfolio of credit exposures increases. Moreover, usually borrower's specific information and aggregate macroeconomic information is also correlated since the customer could expect higher revenues when GDP is growing or vice versa.

2.4.2. ALTERNATIVE CREDIT SCORING

The recent banking crisis highlights some of the challenges in predicting default rates by traditional credit screening. One of the difficulties faced in allocating credit to smaller borrowers is that the credit score (as FICO) is primarily based on historical repayment history and is therefore very susceptible to small shocks to borrowers' financial conditions. Thus, it creates difficulties for smaller borrowers in accessing credit (Iyer et al., 2009). The peer-to-peer

[22] FICO 'classic score' ranges from the lowest (300) to the highest (850).

process has a different way of accessing default probability as the approach to tackle the central issue – information asymmetry for a lender (Kregel, 2016). Most peer-to-peer lending credit worthiness assessment processes use special algorithms. They are based on combination of a credit rating (i.e. FICO), various personal information and Big Data, accessible through borrower's online identifications. Miller (2015) confirms that providing more information improves lender screening and reduces default rates for high-risk loans, however, it has little effect on low risk loans. Iyer et al. (2009) research shows that the magnitude of inference from hard and soft information regarding borrower creditworthiness is high and has significantly greater predictive power than the traditional credit scoring.

2.4.3. Factors determining default & interest rates

The focus of this paper is to determine factors affecting probability of default in bitcoin lending, therefore, deeper analysis on this topic has been conducted below. To the best of our knowledge, there is no academic research made on bitcoin lending. As bitcoin lending is offshoot of peer-to-peer lending, similarities within determinants of defaults are expected. It is relevant to find out if this research is in line with academic literature discussing defaults in peer-to-peer and banking sectors' empirical results. Most of the previous empirical studies on p2p are based on individual lenders investing in individual borrowers from personal to small business purposes on major peer-to-peer platforms – Prosper and Lending Club. There are two groups of factors determining funding success, default rate and interest rate changes: "hard information" and "soft information" (Dong, 2017). Most of the empirical researches discussed in this chapter emphasise the importance of credit rating. Li (2016) even defines credit rating obtained from credit bureau as a key factor of a lenders' investment decision. The author's research concludes that higher credit rating is significantly increasing the probability to be funded, while reducing default rates. Polena & Regner (2016), Iyer et al. (2009) and Serrano-Cinca et al. (2015) conducted the most detailed and relevant study on how hard and soft information variables can influence the probability of default. In Table 1 findings for all credit rating classes, methods and data sets used are presented. Polena & Regner (2016) specify that even though most of the Loan/Borrower characteristics can be used to predict loan's default changes, few of the determinants differ between credit risk classes. The authors conclude that the "length of credit history" importance is significant only for borrowers with high credit rating, while "revolving credit utilization", "delinquency in past 2 years" and "number of characters" describing a purpose are only significant for low credit ratings. Serrano-Cinca et al. (2015) show that credit grade is a significant determinant of default rates, however, additional information improves the explanatory power of the model. Lastly, Iyer et al. (2009) highlight that lenders are able to predict default with 45% greater accuracy than what is achievable just based on the borrower's credit score, the traditional measure of creditworthiness used by banks. This shows that credit score cannot fully capture Prosper listings' creditworthiness along dimensions, as incorporating hard and soft information predicts default more accurately. The authors add up that soft information is significantly more important for lower credit rating classes as the possible traditional credit verification process is sometimes hardly reachable. These results show that non-expert market participants collectively perform rather well and might be a credible threat for the traditional banking system.

TABLE 1. SUMMARY OF BORROWERS' DEFAULT DETERMINANTS

Name of Study	Data Set	Method used	Findings
Polena & Regner (2016)	2009-2015; Lending Club; 36 months.	Binary Logistic regression	Annual income, debt-to-income, inquiries in past 2 years, loan purpose Credit Card, loan purpose Small Business, Number of characters, Length of Credit History
Iyer, R., Khwaja, A.I., Luttmer, E.F.P. & Shue, K. (2009)	2007 - 2011; Prosper; 36 months.	Binary Logistic regression; Goodness-of-fit test	**Hard:** number of current delinquencies; no of credit inquiries last 6 month; amount delinquent; debt-to-income ratio; number of delinquencies last 7 years, number of public records, last 10 years, homeownership dummy; date of residence; length of employment status; personal annual income; borrowers occupation **Soft:** borrowers max interest rate; listing category; member of group dummy; group leaders reward rate; duration of loan listing; image; text characters no; percent of listing as signs; number of friends endorsements;
Serrano-Cinca, C., Gutiérrez-Nieto, B., López-Palacios, L. (2015)	2008-2011; Lending Club; 36 months.	Cross Tabulation, T-independent test, Cox, Logistic regression.	Grade, loan purposes, accommodation situation; interest rate, annual income, credit history variables, credit history length. delinquencies 2 years, inquiries last 6 month, public records, revolving utilization, open accounts, loan amount to annual income, annual instalment to income, debt to income

On the other hand, Mild et al. (2015) demonstrate contradicting results to Iyer et al. (2008) findings. Research based on the Danish myc4.com p2p platform, concentrating on loans to microfinancing reasons within the Africa region, demonstrate that the market itself is not able to price the risk of default at all. However, possible explanation of different outcomes could be due to the limited availability of hard banking data in Danish platform case.

Ravina (2012) conducted further research concentrating on soft information importance. Analysing Prosper data from 2007, the author emphasises the presence of discriminatory lending. A beautiful applicant is 1.59% more likely to be funded and pay lower interest rates even though there is no significant difference between probabilities of default with a similar credential average borrower. Therefore, author concludes that soft information as beauty, race, age and personal characteristics affect lenders' decision. However, Duarte, Siegel & Young (2012) research using larger sample presents that there is a little role for borrowers' perceived attractiveness. Moreover, the authors concentrating on a trustworthiness concludes that trustworthy looking borrowers get better credit scores (for top quintile, 136 basic points lower rate) and higher probability to be funded. However, biased results are possible as research was based on fairly small survey consisting of 25 independent candidates. Furthermore, Lin et al. (2013) found that friendship has a significant impact to funding success, lower interest rates and a relationship to default rates, as friends with credible signals of credit quality determine less default rates for a borrower. Furthermore, while Michels (2012) concludes, that adding any unverifiable information reduces borrower's interest rate by 1.27% and increases bidding activity by 8% in the Prosper platform, Weiss, Pelger, & Horsch (2010) argue that all non-verified variables do not possess any significant influence on the dependent variable. Weiss et al. (2010) confirms the hypothesis that screening of potential borrowers is a major instrument in mitigating adverse selection in p2p and preventing the online market to collapse. Different results between authors in the same platform can be explained by the December 20th, 2010 structural change in the interest rate setting process. Instead of a Dutch auction[23] process Prosper switched to posted price mechanism[24], which according to Wei and Lin (2016) caused the higher probability of being funded and deteriorated loan quality after the change. Furthermore, investors' lending decisions show a herding effect. Herzenstein, Dholakia & Andrews (2010) research shows strategic herding behaviour being present in the Prosper platform based on the data from June 2006. By estimating logit models for every bid in the sample, the authors observed that a 1% increase in the number of bids resulted in a 15% increase in the likelihood of additional bids. The effect is minimized when the loan reaches fully funded

[23] A situation in which two or more groups compete to see who can reduce an amount the most (Cambridge dictionary).

[24] The relationship between the supply of or demand for a particular product or service, and its price (Cambridge Dictionary).

stage, since only a 5% increase is likely for additional bids. The authors emphasise that there is a positive correlation between the subsequence performance and the herding effect, which leads to the greater likelihood of borrowers paying back on time. Thus herding benefits lenders both, individually and collectively.

As aforementioned, most of the studies discussed have been conducted within two main U.S. peer-to-peer platforms – Prosper and Lending Club. However, Meteescu (2015) defines these platforms as exclusive, as they state requirements for participation. These requirements include: the acceptable debt-to-income ratio, credit history longer than 36 months, limited number of credit inquiries in last 6 months as well as minimum FICO of 660 in Prosper and 640 in Lending Club. The author discloses that only 10% of loan applications are funded. Gonzalez & McAller (2011) define that there is a significant basic characteristics differences between loan amount, maturity, interest rates, credit rating and experience within borrowers between Zopa and Prosper platforms. These differences should increase even more between platforms, which are concentrated only on the borrowers who have access to standard banking variables (like Prosper, Lending Club) and for those who are more flexible and enables lenders to invest even in microfinance institutions (like Kiva.org, myc4.com). Dorfleitner et al. (2016) examine two different platforms in Germany. Auxmoney allows borrowers to apply for a loan without providing credit score, while Smava strictly requires it. The authors distinguish the differences within the results of the investor's reaction to the soft information as description texts when deciding upon funding – an effect that is present in Auxmoney, while non-existant in Smava. The extent of reacting appears to depend on the platform's hard information requirements for loan applications. By following the soft information, the investors do not act irrationally in the sense that the repayment behaviour of the granted loans is almost solely dependent on hard facts. Some soft factors may even help to identify debtors with a good level of creditworthiness. Therefore, p2p platforms can indeed provide loans for people who otherwise would not be able to receive a loan.

In comparison with traditional lending, Emekter et al. (2015) found that Lending Club borrowers make less money, but are able to have a higher debt-to-income ratio compared to the U.S. national average from the 2007-2012 data. The authors showed no significant difference between default probability, however, distribution of FICO scores of 750 and above is only 16.9% while 37.73% is the U.S. national average. Jimenez & Saurina (2004) studied the relationship between loan size and risk within 3 million Spanish banks loans. The research disclosed a negative relationship, while the larger the loan analysed the higher the probability of default, as the repayment capability of the borrower and possible loss matters. Chen et al. (2013) examined the relationship between bank size and the bank's ability to use soft information while dealing with small firms. The results suggest that a small bank's manager would have higher incentive in extending small business loans over large banks.

Lastly, the return on investment (ROI) is an important factor as it shows if peer-to-peer platforms provide appropriate interest rates for risk exposures. Klafft (2008) explains that opportunistic behaviour for borrowers to exploit inexperienced lenders is present and lenders suffer, as overall investment performance is not satisfactory in most grade groups in Prosper. Mild et al. (2015) add that 42% of the explained variance, which is sufficient to reduce information asymmetry, is not transformed into smart investment decisions, as lenders suffer from cognitive limitations and biases. Emekter et a. (2015) research on Lending Club provides similar results and the authors conclude that increasing the spread on riskier borrowers may lead to more severe adverse selection problems and higher default rates. On the other hand, Polena & Regner (2016) show that a well diversified peer-to-peer loan portfolio earns higher ROI than a bank's savings. Klafft (2008) adds that if investors in Prosper would take into account simple investment rules like no investments in borrowers with delinquent accounts, no debt-to-income ratio above 20% and no inquiries within the last 6 months, positive returns would be assured for all the ratings except the high-risk and higher than the alternative investments such as 3-year-treasuries (2006-2007 data).

In brief, the common findings of the papers reviewed determine that the probability of default is best explained with the combination of both soft and hard data, while the results can vary within specific platforms, countries and regulations. This paper is established based on the previous literature, since we employ some of the variables presented in those studies. However, contribution to the current research materializes through the application of the same models within the new market segment – bitcoin lending.

3. INSTITUTIONAL BACKGROUND

For the general understanding and comparison purposes, peer-to-peer and bitcoin lending markets have been analysed in the following chapters.

3.1. ALTERNATIVE FINANCING MARKET

The first online lending platform – Zopa (www.zopa.com) was launched in 2005 in the UK, while by 2015, the number of alternative financing platforms reached around 96 (Zhang et al., 2016 (4)). The global shift to alternative financing increased significantly through 2013-2015 (Zhang et al., 2016(3)). For example, in 2015 the alternative finance consumer lending was equivalent to 12.5% of traditional lending in the U.S, while in comparison, it accounted only for 1.65% in 2013 and 3.8 % in 2014. Zhang et al. (2016 (1), (2), (3)) disclosed the alternative financial industry's growth rates to be 72% in Europe, 97% in the Americas and 313% in the Asia-Pacific region within 2015. More than 95% growth accumulated due to substantial development rates in key markets - China, UK and US. General explanations for rapid growth are the significant shift to the internet user base and the active social media environment, growth of e-commerce market, incomplete regulations and support/institutional ownership with the major companies (e.g. Alibaba in China) playing influential role (Zhang et al., 2016 (2)). The trend to continue to take up a larger market share of U.S. consumer credit is foreseen (Zhang et al., 2016 (1)). However, market is still in the development stage and different challenges are faced through the regions. The p2p market is regulated differently depending on the country: while China barely has any regulations and just planning to tighten them (Ruisha, 2016), the U.S. is lightly regulated with a need to educate consumers about the risks they are exposed to (Williams, 2016). Unregulated online financing markets are more exposed to fraud, crime and closedowns of platforms. For example, in 2016 one of the largest peer-to-peer lending service closures in China caused $7.6 billion dollars of loss for investors (Dong, 2017). Furthermore, Deloitte (2016) research argues that banks have a structural cost advantage and when credit environment will normalise to rates and spread returns to pre-crisis levels, the cost incurred in peer-to-peer credit transmission might increase by more than bank lending.

In general, the alternative finance's global market is going through the testing stage (Zhang et al., 2016 (3)). The rapid growth and maturing of the market in some regions increases competition from within and from outside (i.e. financial intermediaries' sides) of the industry.

Uncertainty within macroeconomic conditions, challenges acquiring high-quality borrowers and future deal-flow increase over time, while the cost of capital is likely to rise, with increasing institutionalization, providing challenges for the future (Zhang et al., 2016 (3)). Due to substantially increasing lending market share, investors and regulators should demand for the scrutiny within the credit scoring allocation and due diligence processes. The regulatory side is constantly developing, which adds a short time of uncertainty, but should potentially offer longer-term stability. Creative innovation, financial inclusion and transparency, increasing capabilities on credit risk scoring and controls, and great customer service should sustain the momentum to achieve sustainability (Zhang et al., 2016 (3)).

3.2. Bitcoin Lending platforms

Bitcoin lending platforms are still at a young stage, the first one created just in 2013. These lending platforms are places in which you are able to borrow from someone and lend to someone in bitcoins or bitcoins pledged in fix BTC/USD exchange rate. The biggest, most active and the most developed is German based Bitbond (www.bitbond.com), providing loans for individuals rising capital for small business' purposes, eager to attract institutional investors, and it is also regulated under German Federal Financial Supervisory Authority. It has already originated more than 2000 loans from around 120 different countries. There is a considerably bigger platform BTCJam (market leader), which has facilitated more than 17,000 loans until the middle of 2016, however, data is unavailable to reach and there is no clear information about its activities. The webpage has not been updated and no new loans were generated. Possible reasons for the closure or inactive current stage are tightened government regulations (increased scamming), temporary freeze or just system upgrade, because its users have announced that withdrawal and pay-outs are still possible. Nevertheless, since it is not fully functioning, it would be inappropriate to rely on and trust this platform for further research. Other platforms growing in importance are BitLendingClub originated in Bulgaria (www.bitlendingclub.com) with around 1000 funded loans, also for small businesses; BTCPop (www.btcpop.co) offering instant loans, investment pools and collateral tied loans; Getline (www.getline.in); Nebeus (www.nebeus.com); Wayniloans (www.wayniloans.com) originated in Latin America and some others. However, not all of them are providing full data of their transactions and relevant statistics.

In order to take a loan, the borrower has to provide personal details, as well as government supported identification and credit card verification. Since the main interest in this research is Bitbond platform, all details will be discussed about it. Borrowers in this platform are private individuals taking loans mainly for business purposes or freelance job activities. The borrower has to provide information about his financial background and also additional information such as their type of employment, if possible credit score received from credit bureaus (for which the borrower has to pay by himself). Moreover, connection of the personal PayPal account, eBay feedback score and other online identification profiles have to be provided for Big Data collection process and increase in credit rating. Lastly, country of residence and payment history of bitcoin loans, if it exists, has to be provided. Bitbond's founder Albrecht Radoslav states the importance of credit scoring process, as the more accurate assessments will result in lower default rates, and higher returns for investors, which should further spur on growth (Alois, 2016). The credit rating assigned by Bitbond varies from A to F. According to Bitbond grades between A-C are within the investment grade, while D-F – speculative ones. Letter A represents the highest value (low probability of default), while F categorizes as a highly speculative (high default probability) or as non-measurable due to the lack of information provided by the borrower. In Bitbond, the borrower does not have to comply with the minimum requirements, as FICO score higher than 660, or debt-to-income ratio limits. However, applying for Credit Bureau rates and providing them on application would help to increase credit rate, if borrower has appropriate credit history.

Furthermore, nominal interest rates are set according to the borrower's grade and can vary due to the loan term. These rates are fixed between the borrower's grade and the term of the loan and their distribution can be seen in Appendix B. Bitcoin loans typically carry hefty interest rates in the 8%-44% range, highest being for the F grade. The loan term can vary from 6 weeks to 60 weeks. For 6 weeks there is a single repayment schedule and this is a zero coupon loan. Other loans are repaid monthly with constant annuity, so they are an amortizing type, however, the option of early repayment[25] exists and is often used within the BTC based long-term loans. According to Klafft (2008), early repayments significantly decrease loan portfolio default rates. Moreover, a loan amount's minimum value is 0,1 BTC, while its maximum depends on the borrower's personal debt capacity, all loans outstanding and ongoing loan requests. BitBond

[25] Not available for 6 weeks loans; available for longer maturity, however, before first payment of the loan.

also states that the denomination of the loan is 0,01 BTC and the investor's minimum bid value is also 0,01 BTC.

A default occurs when the loan is not repaid or is repaid only partially 90 days after maturity. Since the system is still very young, there is not yet any debt collection procedure set, but as the founder of Bitbond Albrecht Radoslav (2015) states, it will change in the near future. Bitbond discloses that the current debt collection process is based on regular payment reminders via communication tools (e-mail, phone or SMS) shortly after the payment is overdue. The identity of the borrower is disclosed fully to the lender just in case, when the loan is defaulted upon, so it gives the lender a chance to take any legal action.

Borrowers also pay a loan origination fee depending on the loan maturity and can be as follows: for the 6 weeks loan borrower pays 1% fee of the funded amount, while for the 60 months - 3%. These fees are rather low compared to other lending options, which gives an advantage to bitcoin borrowing. Clear communication is also relevant in the Bidbond platform, which discloses that the reduction in grade might be stopped, if the borrower escalates its future temporary insolvencies with a valid reason to the lenders in advance. Bitbond thus faces steep challenges - convincing loan investors that they stand a good chance of getting their money back and can earn healthy returns. Additionally, the lender is not paying any fee for investing bitcoins.

Lastly, since everything is done through the Internet, automation reduces manual processes, which in turn reduces the overall operating cost. Lichtenwald (2015) affirms that bitcoin lending allows you to do more comparing with the usual p2p lending. He introduced the following advantages: 1) bitcoin loan can diversify your portfolio globally, which gives access for lenders to higher interest rates (Appendix A), and 2) it provides lower fees for investors or borrowers. Bitcoin lending is free from deposits, so it is excluded from any government fees and bank capital requirements. Jose Caldera, a vice president at IdentifyMind Global, which specializes in risk management services, said that the bitcoin loan platforms will attract borrowers and lenders who are on the fringes of the financial system (Wack, 2015). Therefore, it is believed that these platforms suit more for developing countries, where people have problems in obtaining p2p or bank loans, since they either do not have a bank account or access to banking services, or there is no p2p platform in that country. On the contrary, according to BitBond statistics, around 57% of the loans were issued in developed economies until now, but it might change in the near future. Possible reasons could be that due to the still undeveloped market, first users were risk-loving people having enough income to try how it works, also due to interest in new technologies. Nevertheless, the probability that people from developing countries will use bitcoin loans more often is increasing. New platforms are establishing in Latin America and other developing countries, also these platforms provide non-discriminatory access for consumer loans and due to common negative credit rating for people in these countries, it is the only option letting you generate your own credit score in order to obtain the loan. One more important advantage of bitcoin lending is the time of obtaining the loan – it can take up to some minutes to get the money regardless of where you are, thus reducing the transaction costs and exchange fees.

4. DATA & METHODOLOGY

4.1. DATA

The raw data received from the BitBond Platform covers the period from June 2013 to March 2017. The sample has been extracted through the analytical tool (API), which aggregates all the historical data about funded loans whose status (defaulted or not) is provided by the Bitbond. Overall there are 4573 loans, from which still active or cancelled loans (e.g. "current", "cancelled", "expired", "funded", "in funding" and "late 30 days") are removed leaving 1449 loans in total. 62,7% of loans were successfully funded, which is a relatively high coefficient compared with only 10% of p2p Prosper and Lending Club (Mateescu, 2015). The "late 90" loans category was divided into possibly defaulted and still repayable as Polena and Regner (2016) mention that more than 75% of loans with the status Late (31-120) tend to default in Prosper. The tendency to delay on payments is deliberated with an accumulative measurement "days recording the late payment" and it is believed that 15 loans from "late 90" category should be added to the defaulted loans sample as they are more than 120 days late to be paid, in overall time, throughout their existence. The possible limitation of the research exists due to the moderate amount of data and inability to observe economic/business cycles, however, empirically assumed significant results can be drawn as the dataset is large enough to investigate.

Table 2 below shows the available variables from the Bitbond platform and their explanations, which are used in the empirical study. The data is categorized in Borrowers assessment, Loan characteristic, Borrower Characteristics and Borrower Indebtedness groups. Previous studies on the p2p market by Lin (2016), Serrano-Cinca et al. (2015), Polena & Regner (2016), Iyer at al. (2009), Michael (2012) and Dorfleitner et al. (2016) found that variables such as grade, interest rate, loan purpose, loan amount, number of characters in the description, annual income, employment type and borrower's indebtedness are relevant for predicting the probability of default, and so they were chosen for this research. The availability of other significant variables found in p2p was limited to what the Bitbond provides within their API tool. For example, Iyer et al. (2009) and Serrano-Cinca et al. (2015) define credit history variables, such as past delinquencies or public records, as one of the determinants influencing default rates. However, all credit information within Bitbond is already accounted in determining the borrower's credit rating and is kept privately. The only credit history related information found is payments on time, payments late and payments overdue, which is updated constantly, however, on the data collection date it represents post-ex information. As it is not available to retrace variable's true value from the loan's issuing point, this information will be excluded from the analysis.

Other additional variables such as loan term, base currency, employment industry, developed, developing and in transition country of origin have been added to the research, as this data was available and is relevant to test. Firstly, loan term is added in order to see if there is a significant difference between defaulted and fully paid loans in terms of its maturity (i.e. control variable). As mentioned before, loan term is one of the variables setting nominal interest rates. Thus, it will be included within the borrower's assessment group as one of the key aspects-lenders are evaluating. Secondly, the industry, in which borrowers are involved, provide the possible information about the sectors most related with defaulted loans. Using industry variable might help to see the safest/riskiest industries of small business lenders should account for. Bitbond provides information that the industries' classification is given in line with Statistical Classification of Economic Activities in the European Community, Rev. 2 (2008). Thirdly, as there is a general belief that developed countries are less risky than developing, a dummy variable, based on the UN country categorization from World Economic Situation prospect 2016 report, is added to determine if there is any significant difference. Lastly, the loan can be listed either in USD or BTC, depending on what base currency the borrower chooses. The opportunity to pledge the loan to the fixed BTC/USD exchange rate in order to eliminate bitcoin currency volatility exists from 28/12/2014. Bitbond provides information that this change attracts more borrowers and lenders who are skeptical about the BTC currency stability. A dummy variable was added to measure if there is a significant difference between the base currency and if bitcoin volatility is one of the explanations of the default rates. It is expected in general that bitcoin could be a cause of higher default rates. As the BTC/USD exchange rate was increasing throughout the estimated sample period, borrowers' increased repayments might lead to not fulfilling the obligations. On the contrary, data shows that loans distribution between the USD pledged and the BTC loans after 28/12/2014 is similar. Therefore, the assumptions can be made that either investors believe in the BTC's future, its usefulness as a foreign currency hedge discussed in part 2.2, or they had not correctly evaluated its volatility risk and possible consequences. Moreover, Bitbond informs that if the amount is kept in the BTC, the bitcoin loans itself do not bear the volatility change as investors already have bitcoins in their wallets and tend to just lend from what they already own. Currency volatility risk only exists if exchange occurs. Borrowers have an option to repay the loan earlier. Closer data investigation shows that opportunistic behavior exists. Some borrowers utilize speculative strategies and tries to pay out the loan amount fully when the BTC/USD exchange rate is lower, especially with longer-term loans. Sometimes it would significantly reduce lenders ROI, if the exchange of currencies would be employed.

Two subsamples (before and after) have been made for the continuous variables analysis due to the significant increase in fixed interest rates at 28/09/2015. BitBond does not provide any communication about the reasons of interest rate increase. The possible assumptions could be: a substantial increase in volume (Appendix B); change in macroeconomics factors (e.g., slight increase in inflation); and a competitive strategy to attract more lenders based on higher ROI or increase of nominal interest rates as more reasonable compensation for high default rates even within the investment grade loans. For example, 6 weeks B graded loan were assigned 11,15% nominal interest rate before the interest rate change and 20.93% after. While a F graded 6 weeks loan's nominal interest rate increased from 40,48% to 44.17% (Appendix B).

Furthermore, some transformations of the data were applied in order to be able to compare it. Monthly income was converted to annual income. Provided monthly salaries were denominated in the country of origin currency, so the translation into USD using the most recent exchange rates as of 27th of April, 2017 provided by the World's Trusted Currency Authority was performed. Loan amount to annual income ration was calculated after the adjustments to loan amount and annual income (converting into US dollars). Lastly, all BTC based loans were transformed to USD by using exchange rates of the loan-funding day. Daily exchange rates were obtained from the historical data provided in the investing.com database.

TABLE 2. VARIABLES USED IN THE STUDY.

Dependent variable	**Definition**
Loan status	Fully-paid (0) or defaulted (1)
Independent variables	**Definition**
Borrower Assessment	
Grade	Bitbond categorizes borrowers into five grades; A(1), B(2), C(3), D(4), E(5) and F(6); A being the safest.
Interest Rate	Interest rate (APR) on the loan
Loan term	6 weeks (1), 6 months (2), 12 months (3), 36 months (4), 60 months (5)

Loan characteristics	
Purpose	6 loan purposes: consumption, education, refinancing, renovation, working capital and other (for detailed explanation see Appendix B)
Loan amount	Stated amount applied for by the borrower
Purpose description	Number of characters used to describe the purpose as additional explanation
Base currency	An option to fix the exchange rate to current USD/BTC level is possible. The loans are divided between BTC and USD pledged ones.
Borrower characteristics	
Annual income	Monthly income provided by the borrower during appplication multiplied by 12
Employment type	5 types: salaried, self-employed, studying, retired and unemployed
Employment industry	Industries: accommodation and food, administration and support, agriculture, arts and entertainment, construction, education, electricity, extraterritorial organisations, financial and insurance, financial services, household services, human health, information and communication, manufacturing, mining, professional and scientists, public and defence, real estate, transportation, water and waste, wholesale and retail, other services
Country	3 types: developed, in transition, developing
Total identifications	Number of identifications provided by the borrower such as Facebook, Amazon, Coinbase, eBay, Google, LinkedIn and similar.
Borrower Indebtedness	
Loan amount to annual income	Adjusted loan amount in USD divided by converted annual income to USD.
***(.)** – coding used in empirical research part.	

4.2. METHODOLOGY

The aim of the research is to analyse the relevance of the information provided by the Bitbond lending site for the lenders' decision-making and what can influence lower information asymmetry, thus appropriate methods needed to be chosen. Each borrower's loan is rated with a grade, which is capturing the risk of default to reduce information asymmetry for investors. A lower grade should lead to a higher default risk and a higher interest rate. Therefore, the relationship among either the grade assigned or interest rate and default risk will be examined with the help of the loan term and additional explanatory variables.

Since the dependent variable default is dichotomous, a linear regression would not be suitable to capture its dynamics. Therefore, logistic regression is used for the main analysis when one variable is binary and categorical. Crone & Finlay (2012) found that "the logistic regression is a well-established technique employed in evaluating the probability of occurrence of a default" (cited in Serrano-Cinca et al., 2015). Various analysis made on the p2p lending market also used logistic regressions (Serrano-Cinca et al., 2015; Guoa, Zhoub, Luoa, Liuc & Xiong, 2016; Dong, 2017; Polena & Regner, 2016), which indicates its suitability for this research. The goal of logistic regression is to explain the relation between X_i explanatory variables and outcome Y_i, which can obtain the value 1 if there is default, and 0 otherwise. Therefore, for Y_i to obtain the value of 1 there is probability of pi and for 0 there is a probability of ($1-p_i$). Overall the probability of default would be estimated by the inverse logistic function:

$$p_i = \frac{1}{1+e^{-x_i\beta}} \tag{1}$$

Where x_i are jointly independent observations for all X_i explanatory variables (i=1,2,3..) and β is regression coefficient, though the intercept for the first observation. Logistic model is based on the cumulative logistic probability distribution function $F(z_i)$, where z_i is the value of independent variables. While linear regression's coefficients can be directly interpreted, the estimate of the effect of the independent variable to changes in the probability of default in logistic regression is computed with the help of marginal effects. It is the derivative of the estimated regression function with respect to the independent variable of interest. Marginal effects are estimated by the following formula:

$$m_k^{logit} = \beta_k F(z)(1 - F(z)) \tag{2}$$

Where β_k is the regression coefficient and F(z) is the predicted probability at the means. Since the dataset contains both discrete and continuous variables, the interpretation between the two can differ. For a discrete case the interpretation is direct – how the probability of default occurrence changes when the independent variable changes in its value from 0 to 1 and etc. For a continuous variable case, instantaneous rate of change is measured. As Williams (2017) indicates, marginal effect may or may not be close to the effect of one-unit change, therefore, relatively little attention was received in some sciences in order to estimate and interpret these changes for continuous variables case. Furthermore, since the main statistic program used (EViews) does not automatically calculate marginal effects, they were estimated manually just for the discrete variables.

Other parts of empirical research follow Serrano-Cinca et al. (2015) paper investigated for the p2p market and their tests applied, since it is believed that these tests provide relevant information regarding the predictability of default and the explanatory variables influence on default. Moreover, with the help of the following tests the hypotheses of the research can be investigated. Thus, the empirical research consists of:

- Choosing explanatory variables by applying Pearson's correlation coefficients for continuous variables & Point-biserial correlation coefficients for discrete variables. Pearson's correlation coefficient measures the linear relationship between two variables and can obtain value between ±1, where 1 means total positive correlation (-1 total negative) and 0 indicates no linear relation at all. Point-biserial correlation is the relationship between continuous-level and binary variables. A number higher than ±0.8 would indicate serial correlation between variables, which induce a multicollinearity problem.

- The association between explanatory discrete variables (grade or other categorical variable with loan status) test performed using cross tabulation. Michael (2002), defines cross-tabulation as "a joint frequency distribution of cases based on two or more categorical variables", also referred to as the contingency table analysis. A variables' independence (association) is determined by the Chi square statistic ($\chi 2$). Michael (2002) states key assumptions for the chi-square test as: a not biased sample with independent observations (i.e. sampling of one observation does not determine the other's choice), "mutually exclusive" row and column variables including all observations and large expected frequencies. The null hypothesis indicates no relationship, while the alternative states that classifications are dependent. Therefore, if p-value is lower than the significance level, the relationship between discrete variables (for example: grade A defaulted & grade A fully paid) exists.

- An explanatory study on the continuous variables is performed by disclosing the univariate means and the standard deviations for defaulted and non-defaulted loans. The independent-samples t-test (Levene's Test) compares the means or medians between two groups for the same continuous variable (i.e loan amount) and shows if there are significant variances between defaulted and fully paid loans. There are three possible approaches for calculating overall means (Zij) in estimation of Levene's test: using mean, median or timed mean (Sandell & Karllsson, 2016). In order to have robust results with non-normal data as logistic regression, the authors recommend using the median approach. Gereral form of Levene's test statistics:

$$W = \frac{N-k}{k-1} \times \frac{\Sigma_{i=1}^{k} n_i(\bar{Z}_i - Z_{..})^2}{\Sigma_{i=1}^{k}\Sigma_{j=1}^{n_i}(Z_{ij} - \bar{Z}_i)^2} \tag{3}$$

Where $\bar{Z}_i$ is group of means of Z_{ij} (one of three approaches) with j=1, ..., n_i and Z.. is the mean of all N values Z_{ij} (Sandell & Karllsson, 2016). Therefore, if Levene's test p-value is lower than the significance level, the null hypothesis of equal variance is rejected and the significant difference between the continuous variables exists (i.e., loan amount of defaulted loans is significantly different from loan amount of fully paid ones).

4.2.1 HYPOTHESIS

In order to tackle the central issues, such as reducing the information asymmetry for the lenders and factors explaining loan defaults, several hypotheses have been investigated:

H1: Relationship between credit grade (A=1, …, F=6) and the risk of default (default=1) is positive;

H2: Relationship between nominal interest rate per two subsamples and the risk of default is positive;

H3: Relationship between loan term and the risk of default is positive;

H4a: Loan characteristics such as purpose, its description, loan amount and base currency chosen are related to the probability of default in bitcoin lending;

H4b: Borrower characteristics, such as annual income, employment type, employment industry, country of origin and total identifications provided are not all related to the probability of default in bitcoin lending;

H4c: Personal indebtedness such as loan amount to annual income is related to the probability of default in bitcoin lending.

The first hypothesis indicates that the worse the grade is assigned by the bitcoin lending platform, the higher the chance of default. For the second hypothesis the expected relationship is therefore positive, since the higher the nominal interest rate, the higher the risk of default – higher nominal interest rates provide higher compensation for the possible risk. The third hypothesis states that the loan term is self-explanatory default variable, not included in the credit rating, so it has a positive relation with default – longer maturity loans are riskier, and thus increases the probability of default. The fourth hypothesis can be separated into several investigations of how specific drivers can influence loan defaults. Variables already included in the credit rating (i.e. borrowers' characteristics) should not have influence on the probability of default. Other variables, not directly part of the rating such as loan characteristics and indebtedness, should have some influence on default.

Additional assumptions:

1. Bitbond credit scoring approach using Big Data is effective and significant differences between default rate classes exist.
2. There is a difference between explanatory power in models with nominal interest rates and credit grade.
3. An effect of higher interest rate increases default rates and lowers information asymmetry, thus accounts better for actual risk level.
4. Bitcoin based loans' default rates are the same as USD pledged loans.
5. The main determinants of bitcoin based loans and USD pledged loans are the same.

5. EMPIRICAL RESULTS

This part provides the general finding of the results of the methods applied in the main research. Firstly, differences within distribution of independent variables between fully paid and defaulted loans were examined using correlation, frequencies and univariate mean analysis. Secondly, the hypotheses of default determinants were tested by applying logistic regressions. The results are compared with Serrano-Cinco et al. (2015) research, as it is the newest and most comparable research available.

5.1. EXPLANATORY VARIABLES CORRELATION

Appendix C shows Pearson's correlation coefficients for the continuous variables and point-biserial correlation coefficients for the discrete variables for the two sampled periods. The correlation analysis was performed in order to detect and account for any possible multicollinearity problem.

In the continuous variables case, the only highly correlated variables are nominal interest rate (APR) and credit rating (GRADE) with 0.96 (period 1) and almost 0.94 (period 2) correlations respectively. This result was expected as interest rate is determined by the grade. Therefore, strong positive correlation means that the higher the interest rate, the lower the credit score is (A =1, F = 5). The second highest correlation in the first sampled period is obtained between the loan amount and the total number of identifications (-0.4). However, as the rule-of-thumb, just ±0.8 provides high correlation, thus there is no reason to interpret coefficients smaller than this benchmark and suspect any multicollinearity problem.

For the discrete variable case, the same correlation is obtained between APR and Grade. For the variables of the main interest (grade, loan term and interest rate), there is no other strong correlation found with the other explanatory variables. However, there is some sign that developing and developed countries can influence a different result for the interest rate and credit rating, i.e., in the 1st sampled period, there is around -0.3 correlation with APR and grade if the country is developed (riskier borrowers (worse credit rating, higher interest rate) are related to undeveloped countries), while for developing countries the relation is positive (~0.29). Similar results, even stronger are found for the second sampled period as well. However, the coefficients are still too small to rely on.

Nevertheless, the results seem consistent, because a specific linear relation is expected between explanatory variables and the grade. So all four tables are useful in order to see which variables are affecting the grade, the interest rate and loan term. As these tables present linear relationships between explanatory variables, there could also be some non-linear relations, which can be relevant in specific categories, but irrelevant in other ones. However, the credit rating estimation assigned by the BitBond is kept secretly, so it is hard to know what explains it fully and thus the possible multicollinearity problem can still exist.

5.2 EXPLANATORY STUDY ON RELATIONSHIP BETWEEN LOAN DEFAULTS AND INDEPENDENT VARIABLES

This section provides the investigation within the explanatory variables as relevant determinants for default rates. Differences between fully paid and defaulted loans within independent variables are examined using cross-tabulation Chi-square (for discrete) and mean-standard deviation independent t-test (for continuous) in two subsamples (before interest change and after). In addition, this section provides a general descriptive explanation of the sample data.

The distribution of defaulted and fully paid loans disclosed in table 3 shows the difference between default rates within samples: in full sample 41.4% are defaulted loans, while before interest rate change – 39.5% and after – 45.2%. One of possible explanations of default rate increase after interest rate change is a significant interest raise, which caused borrowing costs to soar and is directly related to a higher probability of borrowers failing to repay (i.e. credit risk).

A cross tabulation in table 3 also displays the joint frequencies of discrete variables. Hypotheses to evaluate whether the independent variables are associated or independent are being tested. The relationship between investment grade loans and fully paid status is observable. While 74,1% of A-grade loans are fully paid, the ratio is gradually decreasing to 50% within F-grade loans, as borrowers within this group are highly speculative or non-providing enough information to be graded. The difference between distribution within fully paid and defaulted loans is statistically significant ($p<0,05$) only for investment grade loans (A-C), while for speculative grade (D-F) the null hypothesis of variables being independent cannot be rejected. These two categories seem relatively evenly distributed – investment grade accounts for 49% of the loans, while speculative for 51%. However, the default rates within investment grade loans for B and C are significantly different – increases from 21.9% (B-grade) to 43.1% (C-grade). Therefore, C grade matches more speculative grade loans as D has a default rate of 48% and F of 50%. Moreover, the difference between C and F grades is lower than between B and C. Thus, the Bitbond grading system separation between investment and speculative loans does not truly reflect the reality and may be misleading for investment purposes. Loans' concentration within C-F grade is 80% with the default status rate starting from 43.1%. This matches the prediction that the bitbond lending market based on risky borrowers is mostly used for speculative reasons. To sum up, the grade assigned for borrowers by the Bitbond does not help to reduce asymmetric information problem. Lenders, especially for C-F graded borrowers, are basically taking 50-50 chance of getting their invested money back and should not fully rely on the grade as a determinant of the default probability. The reason of risky borrowers and possibly clueless about the actual credit risk lenders might be young market, global accessibility (no minimum requirements for getting loan funded exists), lenders' inability to estimate credit risk, without financial experts assistance and poorly developed credit rating system.

Investigating the loan characteristic variables, statistically significant differences between loan term of 6 weeks and 12 months, base currency variables and 'renovation', 'other' and 'investment' purposes are observed. 52% of loans provided have 6 weeks term and 72,3% of them are associated with fully paid ones. All other maturity loans are concentrated more on default side. The Chi-test results of 12 months loans showed statistical significance, which means borrowers with 12 months loans are subjected to default. In general, a longer maturity is subjected to higher default rates, while as bitcoin lending is still a young market the uncertainty increases even more. Therefore, lenders should invest mostly in 6 weeks loans, as any other maturity loans seems to give higher probability of losses than returns. Furthermore, examining the base currency choice, it could be seen that there is no significant difference between taking the USD pledged or bitcoin loan. Both categories are related to fully paid loans with statistically significant ($p<0,05$) differences between frequencies. Therefore, bitcoin currency volatility should not be a reason for higher default. Lastly, most of the loans were taken for investment (37,1%), working capital (25,7%) and other purposes (24,5%). The purpose of 'investment' and 'other' is related to fully paid loans (61,3% and 65,1%) and have significant differences. The riskiest purpose seems to be 'working capital' due to 51.2% defaulted loans. However, as it has no significant difference, it can be treated in the same uncertain category as 'consumption', 'refinance' or 'education'. Therefore, some of the purposes might be significant in explaining default rates.

Analysis of the borrowers' characteristic variables shows that there is a significant difference between developed and developing, salaried and self-employed borrowers, involved in industries such as financial services, information & communication, professional & scientific, manufacturing, education, mining and transportation. As developed (fully paid - 61.6%) and developing (53.3%) countries have a significant difference between defaulted and non-defaulted loans, lenders should not automatically assume that developing countries' loans are riskier. As expected, self-employed and salaried borrowers take 92,8% of the loans and Chi test revealed significantly different results between fully paid and defaulted loans within both groups. Other groups (retired, unemployed, students) are not earning regular income, so the debt-to-annual income or any proof of ability to repay the loan is significantly low, thus getting funded is subjectively difficult. Lastly, the industry variable shows that the 14 categories are related to fully paid loans, while the other 6 are related with defaulted and 2 cannot be tested due to less than 0.5% participation within the sample. Most of the loans are taken by the borrowers involved in the financial services (9,7%), information & communication (20%) or professional & scientific (11%) industries; all of them are positively related to fully paid loans and significantly differ ($p<0,01$). These industries could be defined as the safest, since all of them are related with highly educated people, thus borrowers might have more knowledge about bitcoins and risk in borrowing involved. Mining and transportation are the riskiest classes, as they have significant differences and are highly related to default – 81.8% and 72.2%. Most of all the other categories consist of only up to 4% of all loans taken, which is a relatively small part of the sample in order to make any plausible conclusions.

To sum up, the cross tabulation results and the Chi-square test for the discrete variables conclude that there is a significant difference between fully paid and defaulted loans in the investment grade, 6 weeks loans based on any of the currency and within developed or developing countries. Salaried or self-employed borrowers taken loans for renovation, other or investment purposes within the financial services, information, professional, manufacturing, education industries have stronger and significant relationships with fully paid loans. However, even if considering the safest type of the borrower with the safest loan - grade "B", term "6 weeks", currency "BTC", developed country, salaried, working in financial industry and taking a loan for other purposes - the relationship with defaulted loan is still subjectively high – it varies from 21,9% to 36%. Comparing these results with Lending Club platform (p2p) estimations by Serrano-Cinca et al. (2015), considerable differences are observed. For example, in BitBond 21,9% B-graded loans have defaulted, while Lending Club reports 10,3% for the same category. It is important to highlight that Bitbond defines B-graded loan as low probability to default and as an investment grade, however, the actual percentage of defaulted loans for B grade match more F-graded loans in the Lending Club platform according to the Serrano-Cinca et al. research results. This might lead to the conclusion that Bitcoin loans are exposed to a higher risk, instability and higher default rates, and thus lenders should consider investment only if they have a high-risk tolerance or for speculative reasons. The difference between these platforms should not be caused by bitcoin currency itself as the condition to be pledged to BTC/USD exchange rate exists and the volatility of the currency is eliminated. Plausible explanations of in general high default rates even within the “safest” classes could be:

- high level of successfully funded loans rate in comparison to p2p markets leads to high amount of risky borrowers, thus increase in default rates;
- young, unexplored market, also used for speculative reasons;
- small business loans (bitcoin lending) in general being the riskiest purpose/sector than the individual lending (Lending club) (see Cicna et al., 2015);
- more difficulties in debt collection in the case of default as activities are based globally, leads to more opportunistic behaviour by borrowers;
- Internationally different regulatory systems.

TABLE 3. EXPLANATORY STUDY ON DISCRETE VARIABLES

	Loan Status % (N)					
Predictors	**Fully paid**	**Defaulted**	**%**	**N**	**Chi^2, sig**	**p-value**
Grade						
A	74,1%	25,9%	1,9%	27	6,259	0,012**
B	78,1%	21,9%	17,3%	251	79,207	0,000***
C	56,9%	43,1%	30,0%	434	8,295	0,004***
D	52,0%	48,0%	31,6%	458	0,707	0,400
E	53,3%	46,7%	17,9%	259	1,115	0,291
F	50,0%	50,0%	1,4%	20	0,000	1,000
Loan Term						
6 weeks	72,3%	27,7%	52,1%	755	150,423	0,000***
6 months	49,3%	50,7%	31,2%	452	0,800	0,778
12 months	39,2%	60,8%	13,0%	189	8,894	0,003***
36 months	15,2%	84,8%	2,3%	33	16,030	0,000***
60 months	5,0%	95,0%	1,4%	20	16,200	0,000***
Base currency						
BTC	60,7%	39,3%	61,4%	889	41,036	0,000***
USD	55,2%	44,8%	38,6%	560	6,007	0,014**

Countries (UN)						
Developed	61,6%	38,4%	57,3%	831	44,824	0,000***
Developing	55,3%	44,7%	41,1%	595	6,671	0,010**
In Transition	34,8%	65,2%	1,6%	23	2,130	0,144
Employment type						
Retired	62,5%	37,5%	1,1%	16	1,000	0,317
Salaried	59,3%	40,7%	64,4%	933	32,078	0,000***
Self-employed	57,4%	42,6%	28,4%	411	9,054	0,003***
Studying	56,6%	43,4%	3,6%	53	0,925	0,336
Unemployed	55,6%	44,4%	2,5%	36	0,444	0,505
Loan Purpose						
Renovation	70,0%	30,0%	2,1%	30	4,800	0,028**
Other	65,1%	34,9%	24,5%	355	32,251	0,000***
Consumption	62,5%	37,5%	2,2%	32	2,000	0,157
Investments	61,3%	38,7%	37,1%	537	27,264	0,000***
Refinance	55,9%	44,1%	4,1%	59	0,831	0,362
Education	52,4%	47,6%	4,3%	63	0,143	0,705
Working Capital	48,8%	51,2%	25,7%	373	0,217	0,641
Industry						
Financial services	66,4%	33,6%	9,7%	140	15,114	0,000***
Information & Com	65,9%	34,1%	20,0%	290	29,186	0,000***
Professional & Scientific	65,6%	34,4%	11,0%	160	15,625	0,000***
Manufacturing	61,7%	38,3%	6,5%	94	5,149	0,023**
Education	68,9%	31,1%	3,1%	45	6,422	0,011**
Other services	56,7%	43,3%	14,5%	210	3,733	0,053
Whole sale & Retail	55,2%	44,8%	8,6%	125	1,352	0,245
Public defence	55,8%	44,2%	3,0%	43	0,581	0,446
Human Health	53,7%	46,3%	2,8%	41	0,220	0,639
Agriculture	58,6%	41,4%	2,0%	29	0,862	0,353
Real estate	62,5%	37,5%	0,6%	8	0,500	0,480
Household services	66,7%	33,3%	0,4%	6	0,667	0,414
Water & Waste	66,7%	33,3%	0,2%	3	0,333	0,564
Electricity	50,0%	50,0%	2,1%	30	0,000	1,000
Mining	18,2%	81,8%	0,8%	11	4,455	0,035**
Transportation	27,8%	72,2%	2,5%	36	7,111	0,008***
Accommodation & Food	40,7%	59,3%	1,9%	27	0,926	0,336
Construction	42,3%	57,7%	3,6%	52	1,231	0,267
Admin & Support	46,6%	53,4%	3,9%	58	0,276	0,599
Arts & Entertainment	48,6%	51,4%	2,4%	35	0,029	0,866
Fin. lnst. &Insurance	100,0%	0,0%	0,3%	5	n/a	n/a
Extraterritorial org.	0,0%	100,0%	0,1%	1	n/a	n/a

Number of loans analysed 1449. Defaulted: 600 (41.4%), Fully paid: 849 (58.6%).
*** significant at the 1 % level
** significant at 5 % level

Loan status as a % of each explanatory variable is displayed. '%' indicates the proportion of each variable within its group, while N - total number of observations within the same group. Chi-squared and its corresponding p-values demonstrate the significance level between the difference in loan status for each explanatory variable.

On the other hand, investors might be interested to invest in bitcoin loans, if risk premium is added to the nominal interest rate in comparison to safer options, as risk-return relationship should exist. Table 4 shows explanatory study is based on the continuous variables, where Levene's test on the null hypothesis to see if there is no significant difference between the means.

Firstly, there is an observable difference between the two periods, possibly due to uneven sample sizes – subsample "before" is almost double the number of observations. Loan amount is significant in the first period, while description count, annual income and loan-amount-to-annual-income variables are significant in the second. Nominal interest rate is the only variable highly significant through both samples. The average interest rate before change was 16% for fully paid and 18% for defaulted loans, while after change – 28% for both. Interest rate means are significantly different in both periods ($p<0.05$). As interest rate is fixed, almost the same mean of both fully paid and defaulted loans can be explained by the data distribution – most of the borrowers are within C and D grades and 6 weeks loan term. A significant increase in the interest rate (Appendix B) represents mistrust in the borrowers' creditworthiness within the Bitbond platform regulators, as the spread of nominal interest rates between credit A and F decreased. This is in line with the cross-tabulation analysis, as 80% of the loans are distributed within C-F grade and are subjected to 43.1% default rate, thus the increase in the interest rate seems to be relevant for attracting risk-averse investors.

Increase in nominal interest rate seems to result in different borrowers' allocation from as it is used. Changes in means between other continuous variables in Table 4 shows that higher interest rates attracted the borrowers with higher annual income (also higher indebtedness level). More identifications and longer descriptions have been provided in order to lower the nominal interest rate. Subsequently, borrowers are asking for higher loan amount. Therefore, the change in nominal interest rate gave the incentive for the borrowers to reduce information asymmetry, as more details were provided, as well as possible cut off of lower income borrowers.

In comparison with Serrano-Cinca et al. (2015) Lending club, the after sample outcome is more in line with its results, though quite high differences can be observed between two platforms variables' means. Lending Club reported the mean of the nominal interest rates for fully paid loans of 10.8%, while for defaulted loans – 12.3%, as in Bitbond – 28% for both. The loan amount and annual income are almost twice as high, while the indebtedness ratio was significantly lower in Lending Club platform. Higher quality borrowers within p2p platform could explain the differences as Prosper and Lending Club fund only 10% of loans' applications (Mateescu, 2015), while Bitbond fund 62,7%.

To sum up, within the BitBond data analysed, the hypotheses are partially accepted: interest rates significantly differ between defaulted and non-defaulted loans. Continues variables such as nominal interest rate, loan term, annual income, description characters and borrower indebtedness matter. However, variables such as loan amount and total identification do not seem to be relevant within the data analysed after the interest rates changes. Bitbond is a riskier investment option in comparison with Serrano-Cinca et al. (2015) Lending Club. On the other hand, the average nominal interest rate is around 17% higher than in Lending Club, so risk-return balance exists. However, deeper analysis needs to be performed in order to determine if there are empirical differences within platforms, and if nominal interest rate compensation is covering the actual credit risk. By examining just the variables within distributions in specific classes cannot fully represent reasonable investment decision as possible portfolio diversification is not taken into account.

TABLE 4. EXPLORATORY STUDY ON CONTINUES VARIABLES BEFORE AND AFTER INTEREST RATE CHANGES.

Group Statistics Before interest rate change N= 953	Fully paid		Defaulted		Levene's Test, sig
	Mean	Std. Deviation	Mean	Std. Deviation	
Borrowers assessment					
Nominal interest rate	0,16	0,06	0,18	0,05	0,013**
Loan Characteristics					
Loan amount (USD)	3708,62	1850,59	3380,19	1466,47	0,024**
Description characters	277	247,7	292,12	275,08	0,115
Borrowers Characteristics					
Annual income (USD)	28043	24867,87	25380,2	28596,073	0,421
Total identifications	4,4	2,66	4,25	2,55	0,703
Borrowers indebtedness					
Loan amount to annual income	0,36	0,68	0,36	0,6	0,192
After interest rate change N= 496	**Fully paid**		**Defaulted**		
Borrowers assessment					
Nominal interest rate	0,28	0,05	0,28	0,05	0,046**
Loan Characteristics					
Loan amount (USD)	4981,26	1460,91	4811,23	1457,07	0,966
Description characters	402,06	313,98	396,78	290,59	0,044**
Borrowers Characteristics					
Annual income (USD)	34129,7	34273,42	27053,15	25602,82	0,017**
Total identifications	5,14	1,96	5,07	2,01	0,594
Borrowers indebtedness					
Loan amount to annual income	0,43	0,67	0,61	1,51	0,008***

Number of loans analysed: Before - 953, After - 496. Before: Defaulted: 376 (39.5%), Fully paid: 577 (60.5%). After:Defaulted: 224 (45.2%), Fully paid: 272 (54.8%)

*** significant at the 1 % level

** significant at 5 % level

N indicates total number of observations for each explanatory variable, with its mean and standard deviation for the two loan status groups – fully paid and defaulted. Levene's test demonstrates the significance of variance differences between two loan status groups for each explanatory variable.

5.3. Logistic Regression

Table 5 shows the performance of 9 logistic regression models. Model 1 includes grade and loan term as the only explicit variables, then further models add up other variables classes (loan characteristics, borrower characteristics and indebtedness level) separately until Model 5 with all variables is reached. Models 6-9, on the other hand, use the interest rate instead of the grade.

The grade and interest rate were not used together in the same regression due to their high correlation. Moreover, in order to capture the interest rate increase effect from 28/09/2015, both periods were tested separately. Therefore, Model 6 determines if using interest rate and loan term is sufficient enough to determine probability of default before the interest rate increase, while Model 7 shows if additional information is more accurate in the model designed. Model 8 and Model 9 apply the same idea for the second sample period ("after"). In order to perform the logistic regression analysis, some of the discrete variables were removed from the test as outliers, since they are either biased within one category (fully paid or defaulted) or too small to examine (N<30) (see table 6).

Logistic regressions provide estimated marginal effect coefficients and significance levels of test coefficients. McFadden R-squared is analog to R-squared in linear regression model, however, it is computed based on the maximum-likelihood ratio and can obtain the value between 0 and 1. The values from 0.2-0.4 indicate an especially good model fit (Hensher & Stopher, 1979). An additional goodness-of-fit test measure by means of Hosmer–Lemeshow was used. This statistical test is based on grouping cases into deciles of risk and then comparing the observed and expected probabilities within each decile. Hosmer–Lemeshow p-value higher than 0.05 indicates good model fit to the data.

Model 1 includes only grade and loan term as explanatory variables, which are positive and highly significant. Therefore, this is in line with the first and third hypothesis, that default is more likely when the grade is worse (F=6) and maturity (60 months=5) is longer. However, neither R-squared (0,096) or H-L test (p<0,05) show a good fit of the model, reasonably due to the under fitting problem. Under fitting is often a result of an excessively simple model (Cai, 2014). Therefore, the grade and loan term alone are insufficient variables to explain default and additional information should be taken into account. This result is self-explanatory in the sense that the credit rating does not include any loan characteristic variables such as loan amount. The marginal effect change indicates that there is a predicted 7,76% average increase in the probability of default if the grade is worsening, for example, moving from A to B (as A=1, F=6). On the other hand, the probability of default is predicted to increase by 19,69% if the loan term increases, for example from 6 weeks (1) to 6 months (2). As a popular theory states about borrower's risk, the likelihood that a loan ever enters default decreases as its maturity decreases (Strahan, 1999). Moreover, the loan term seems to effect the default rate changes more significantly than the grade. This could be explained from the previous cross tabulation analysis: borrowers' concentration within C-F grade and 6 weeks term. While the difference between each loan term is visible between fully paid loans (i.e., for 6 weeks – 72% successfully funded, for 36 months – 15.2%), there is almost no difference between fully paid and C-F grade loans (C - 56%, E - 53,3%). Comparing the results with the previous research done on the P2P market, the significant difference in grade importance as a determinant is visible. Serrano-Cinca et al. (2015) model with only a grade as the explanatory variable showed a good fit. The difference in findings can be explained as the Bitbond market is rather young and the ratio of successfully funded to all loans is much higher than in major p2p lending sites, therefore, the assumption of a lower standards selective process of borrowers can be raised. This leads to a higher risk of opportunistic situations, information asymmetry and default rates (see section 5.2). The Bitbond grading system is affected by pooling similar, lower credit borrowers, which are separated within 6 groups and not truly representing the differences between themselves as disclosed in cross tabulation analysis. Thus, lenders mislead to believe that there is a significant uniqueness between a C and F borrower, while actually they might have almost the same probability to default.

Model 2 confirms the hypothesis (H4a) raised that loan characteristics might explain default rates. In addition to the grade and loan term, working capital purpose and loan amount have additional explanatory power. Marginal effects show that the probability of default increases by 21,78%, if the working capital purpose is selected (compared with no working capital), which identifies it as one of the riskiest small business purposes. As Serrano-Cinca et al. (2015) disclosed, small business purposes are the riskiest within any of the individual borrower options, as small business is usually in the developing stage and with high uncertainties on income and profitability. Moreover, as defined in Appendix C, working capital is mostly subjected to paying off debt or funding ongoing operations, where both activities are related to higher risk and probability of default. Since working capital is one of the three main reasons why a loan was taken, it is not subjected to incorrect interpretation due to the small sample size. Another significant variable, loan amount, goes in line with the traditional financial institutions results (Jimenez & Saurina, 2004), while contradicts Serrano-Cinca et. al (2015) findings of its significance. In general, R-squared and H-L tests show that the model has a good fit. Furthermore, it is difficult to interpret the marginal effects on continuous variables (i.e. loan amount or interest rate), as the relationships might be non-linear. Additional to what was discussed in methodology part, if the variable is measured in larger units (i.e. millions), marginal effect does not provide good approximation of a one-unit increase in explanatory variable and as Williams (2017) states, it may or may not be true for small units as well.

Therefore, the marginal effects for continuous variables will not be compared in further research in order to avoid misleading interpretations.

Model 3's results partly agree with the H4b hypothesis raised. R-squared and H-L tests show that it is one of the best-fitted models within the full data set. Most of the borrowers' characteristics are already present in the grade itself, as the variables are insignificant and the only exception is the total identification number, which has negative coefficient. From the marginal effect calculations, the decrease in probability of default by 1,1% would occur, if the borrower provides one additional online identification profile in his application process. However, the limitation of this is that the relevant information within the additional identification account should be measured, however, impossible to obtain.

Moreover, McFadden R-squared and H-L tests show that Model 4 is not a good model and that the borrowers' indebtedness ratio is insignificant, so it does not determine the rate of default. This contradicts the findings of Serrano-Cinca et. al (2015). The reason behind this might be that income is already part of the grade, which should not add additional explanatory power to the default rate. Moreover, income is also relatively larger than the loan amount requested, so the overall ratio relies more on the income part. Additionally, under fitting could cause a model to be insignificant.

Even if overfitting (opposite to under fitting) might be present in Model 5, this model is the best-fitted one within the full data set – its goodness-of-fit increased the most. The results show that most of the variables relevant in separate models are still significant and relevant added up together. In addition to the variables already discussed, borrowers working within industries such as education and transportation became statistically significant. Comparing marginal changes within all models, in model 5 the grade effect on the probability of default is the highest - reached 9,96%.

The difference between Model 6 and Model 8 in McFadden R-squared and H-L tests shows the improved explanatory power of nominal interest rate as default determinant after the interest rate increase. The H2 is confirmed by both models, however, only Model 8 has a good-fit. Loan term is included in the estimation of the models even though it is one of the components determining interest rate, but no multicollenarity was found within these two variables (see 5.1. section). McFadden R-squared on Model 7 and Model 9 show that adding the nominal interest rate instead of the grade with the other explanatory variables increases goodness-of-fit. However, the results are contradicted by H-L test, showing better fit for Model 5. The distribution of fully paid vs. defaulted loans in smaller samples should not be biased, since default rate in full sample is higher than the "before" sample and lower than the "after" one (see Table 5, samples N). As the algorithm of grade estimation is unknown, thus it is difficult to see which of the borrower's characteristic variables determines it the most. Including interest rate instead of grade gives different significant variables within the logistic regressions. Model 7 contains seven additional significant variables comparing to Model 5 including most of the purposes, annual income and additional industry categories. Model 9 shows that loan amount, total identifications and purpose variables are not significant anymore after the interest rate change, however, the borrower's industry variables become more relevant. Therefore, information asymmetry was accounted in the interest rate change itself in order to disclose better credit default risk for the potential lenders. This assumption is in line with the Bitbond strategy to attract more investors, as according to already discussed Klafft (2008) results, market participants are unable to evaluate any additional information properly themselves, which leads to higher default rates and potential platform collapse. Therefore, capturing as much asymmetric information as possible in the grade or interest rate is lowering default rates and increasing trust of the platform.

To sum up, the explanatory model of default is more accurate when the additional information of the loans characteristic is added to the borrower's credit grade. Loan amount, loan term, purpose of working capital, industry of education and transportation as well as the total number of identification are significant determinants of the default rates. Subsample tests (models 6-9) show that interest rate change is accurate and increases the explanatory power of the probability of default. Moreover, McFadden R-square results on these models reveal that the interest rate is a better explanatory variable than the credit grade. However, H-L test contradicts these results, so no concrete conclusion can be made. On the other hand, the logistic regressions' analysis shows that there is no difference between developed or developing countries, which contradict the general assumption that developed countries have safer borrowers. Moreover, base currency as a dummy variable shows that there is no difference or significant relationship between BTC and USD pledged loans.

Additional tests to check the difference between the BTC and USD pledged loans were conducted (Appendix D). The subsamples after 28/12/2014 introduction of USD pledge loans option were examined to determine if there are any significant differences between the default levels as well as variables explaining defaults. As mentioned before, the distribution between USD pledged loans (N=522) and BTC loans (N=458) is almost even. Appendix D shows that the rate of defaulted loans is similar in both subsamples – BTC – 44,97%, USD – 44.56%. Some differences exist, as a BTC loans' default has a significant negative relationship with developed countries (i.e. default reduces if borrowers are from developed countries) and manufacturing sector (i.e. borrowers working in manufacturing are associated with lower default rates). USD pledged loans, on the other hand, have a significant negative relationship with description length and number of total identification while positive with working capital. Thus, providing longer description and access to identification sites lowers default rate, while loan purpose of working capital should be significantly related to default and lenders should consider it. However, both BTC and USD loans are mostly determined by the key variables - grade, loan term and loan amount. Therefore, there is no significant difference between which base currency is used in the agreement and bitcoin currency volatility is not a key explanation of the high default rates.

TABLE 5. MARGINAL EFFECTS OF LOGISTIC REGRESSIONS FOR 9 MODELS

	Full model					Sample 1		Sample 2	
N	Fully paid (0) = 849; Defaulted (1) = 600					0 = 571; 1 = 366		0 = 272; 1 = 221	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Borrower Assesment									
Grade	0,078***	0,091***	0,077***	0,0833***	0,099***				
Interest rate						1,653***	1,969***	1,078***	1,296***
Loan term	0,197***	0,202***	0,208***	0,198***	0,219***	0,201***	0,228***	0,247***	0,296***
Loan characteristics									
Purpose:									
Investment		0,058			0,036		0,333*		-0,181
Refinancing		0,109			0,102		0,352		-0,001
Education		0,153			0,140		0,382		-0,029
Working capital		0,219**			0,191*		0,489**		0,041
Consumption		0,057			0,036		0,489**		-0,234
Other		0,082			0,060		0,339*		-0,078
Loan amount		-0,000***			0,000***		0,000**		0,000
Number of characters		-0,001			0,000		0,000		0,000
Base currency		-0,043			-0,027		0,018		-0,091
Borrower characteristics									
Annual income			0,000		0,000		0,000*		0,000
Employment type:									
Salaried			0,108		0,138		-0,029		0,526
Self employed			0,097		0,132		-0,009		0,475
Studying			0,129		0,129		-0,045		1,123
Unemployed			0,015		0,01		-0,166		0,281
Industry:									
Financial services			-0,087		-0,096		0,133		-0,281*
Information and com			-0,091		-0,106		0,202		-0,463***
Proffesional and scientific			-0,085		-0,112		0,169		-0,324**
Manufacturing			-0,087		-0,09		0,274		-0,516***
Education			-0,177		-0,215*		0,053		-0,351
Other services			-0,027		-0,061		0,219		-0,238
Wholesale and retail			-0,004		-0,044		0,170		-0,209
Public and defense			-0,065		-0,076		0,125		-0,220
Human health			-0,015		-0,027		0,305		-0,246
Transportation			0,254		0,266**		0,739***		-0,267
Arts and entertainment			-0,103		-0,129		0,317		-0,928***
Admin and support			0,076		-0,055		0,408**		-0,217
Construction			0,184		-0,168		0,415**		0,076
Agriculture			-0,123		-0,153		0,162		-0,620**
Electricity			0,119		-0,075		0,329		-0,099
Accommodation and food			0,1106		0,069		0,491**		-0,373
Country:									
Developed			-0,143		-0,108		0,003		-0,047
Developing			-0,133		-0,128		0,024		-0,061
Total identifications			-0,011*		-0,016**		-0,024**		0,001
Borrower indebtedness									
oan amount to ann. income				-0,024	-0,009		-0,041		0,009
McFadden R-squared	0,096	0,113	0,119	0,097	0,138	0,086	0,152	0,112	0,190
Hosmer-Lemeshow Test	0,000	0,239	0,479	0,000	0,645	0,001	0,071	0,930	0,427

*** significant at the 1% level ** significant at 5% the level * significant at the 10% level

Models 1-5 include all samples of loans (N), both fully paid and defaulted. Models 6-9 for Sample 1 and Sample 2 indicate the period before and after the interest rate change both for fully paid and defaulted loans. Each number represents computed marginal coefficients and '*' corresponding significance level. Each model differs depending on the explanatory variables included. McFadden R-squared and Hosmer-Lemeshow Test indicates the model's goodness-of-fit, for the later being higher than 0.05.

6. CONCLUSION

Bitcoin and P2P combination - bitcoin lending - is seen as an alternative financing option to traditional financial institutions due to its lower transaction costs, accessibility for non "bankable" borrowers, time-effective and transparent processes. Since borrowers and lenders are simply put together into one platform, automation reduces processing costs, which are the most important expenses in the banking industry, therefore, it provides a technological advantage for bitcoin lending. It is also attractive as a foreign currency investment due to its international lending and borrowing option, reduced risk for foreign exchange exposure and usefulness as a speculative tool, giving advantage against usual p2p lending. In addition, global diversification, accessibility of higher Return of Investment rates and lower fees distinguish bitcoin lending from p2p markets. The credit rationing problem is reduced through online lending, which explains the growth of this market. On the other hand, the information asymmetry reduction is a crucial issue in this market, since the risk is faced directly by the individual lenders while in the banking industry credit risk management is under the financial institution itself with analysts providing their expertise. Therefore, bitcoin lending platforms face steep challenges to provide quality information about its borrowers and loans in order to reduce credit risk. This can be done by obtaining the information from the platform itself as a grade assigned for each borrower or relying on third party credit scoring.

This paper analyses whether the additional information such as borrowers' and loans' characteristics, without the interest rate or grade in the bitcoin lending platform Bitbond can fully explain probability of default and reduce information asymmetry. An empirical study has been conducted to test the hypotheses on variables influencing probability of default. Descriptive loans' analysis indicates that 80% of the Bitbond's platform is concentrated within C-F credit rating borrowers, with default rates higher than 41.3% and interest rates of 28%, on average. Concentration of risky borrowers might be explained as a still developing market's problem, attracting speculative investors and opportunistic borrowers. Since requirements to get funded are minimal, 63% of borrowers have been funded. Comparing results with the Lending Club's research revealed that Bitbond is subjected to much higher risk, as well as returns. Logistic regressions were set up for 9 different models in order to predict the defaults. The results indicate that there is no clear relation between the grade assigned by the Bitbond and the default, i.e., 20-25% of A-B graded loans are defaulted, while the percentage rapidly increased to 43-50% within D-F grades. Thus, it indicates that lenders, especially within speculative class, are faced with uncertainty and should not fully rely on the grade as a determinant of default probability. The loan term is another factor potentially explaining default – there is an extreme pattern of loans longer than 6 weeks to be subjected to more than 50% default rate. Loan amount, loan purpose as working capital, loan industry as education and transportation and total identification were found to be significant as well. However, there was no significance difference found with annual income, length of description, employment type, between country of origin or base currency choice. Additional research was made on the two subsamples due to interest rate increase and a significant difference was found between the explanatory variables. It might be caused by different borrowers' profile after interest rate change due to their willingness to reduce information asymmetry in order to access lower nominal interest rates. In both periods nominal interest rate indicates a clear relation with default probability, however, there is no significant difference in comparison to the full grade model of goodness-of-fit. Different significant explanatory variables between interest rate or grade based models exist.

To sum up, information provided by the Bitbond platform gives the right to see loans'/borrowers' characteristics, borrowing history, credit grades assigned and success of funding. Therefore, information asymmetry is partly reduced through the qualitative data provided. Nevertheless, bitcoin loans are exposed to higher risk, instability and default rates compared with the usual p2p lending, so lenders should be careful with their investment choice. As the research is limited, possible recommendations for the future study are to include a larger sample of data, use larger time frame and add more additional variables, like soft data, which would increase explanatory power of the models. Moreover, deep and comparative analysis with p2p lending market would provide more insights for actual risk-returns.

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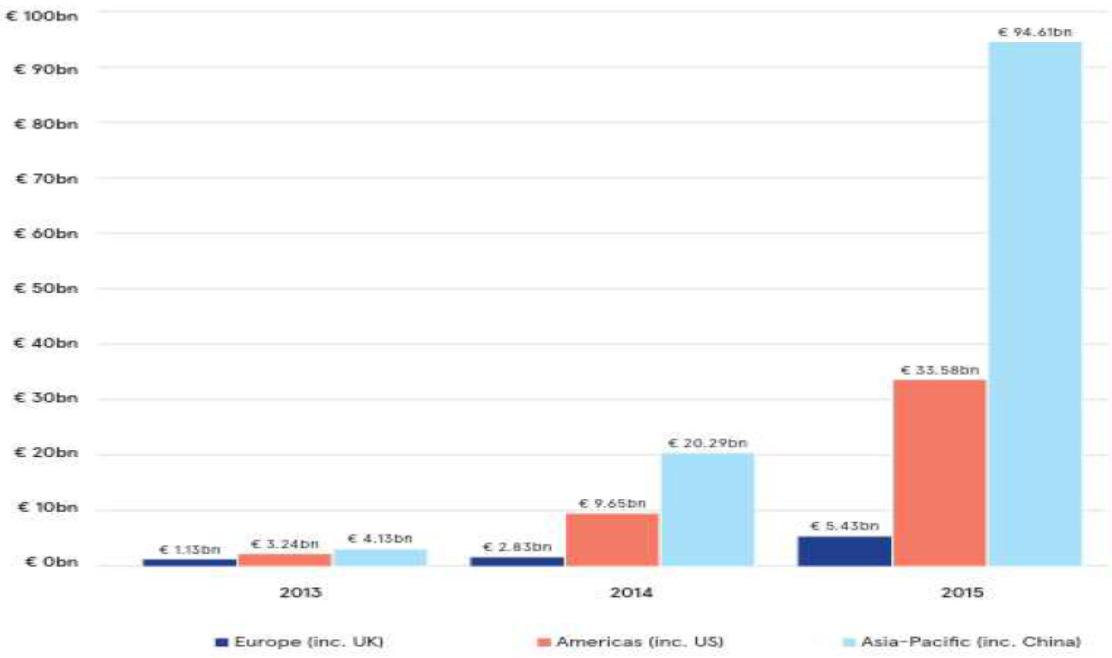
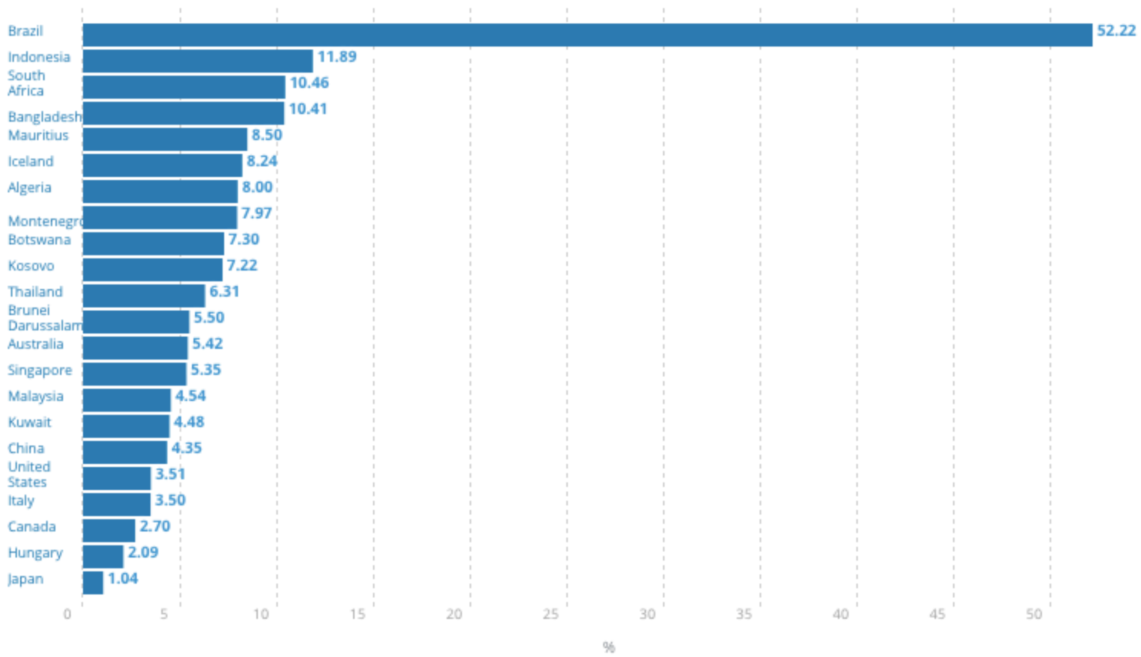
APPENDIX A

Figure 1. Regional Online Alternative Finance Volumes (Euro) 2013 – 2015



Resource: Zhang et al. (2016)

Figure 2. Lending interest rates (%) 2016



Resource: data.worldbank.org

Figure 3. Average USD market price across major bitcoin exchanges. Jan 2009 - March 2017

Resource: blockchain.info

Figure 4. Market capitalization - the total USD value of bitcoin supply in circulation, as calculated by the daily average market price across major exchanges. Jan 2009 - March 2017

Resource: blockchain.info

APPENDIX B

Table 1. Interest rate distribution (%) between two subsample periods

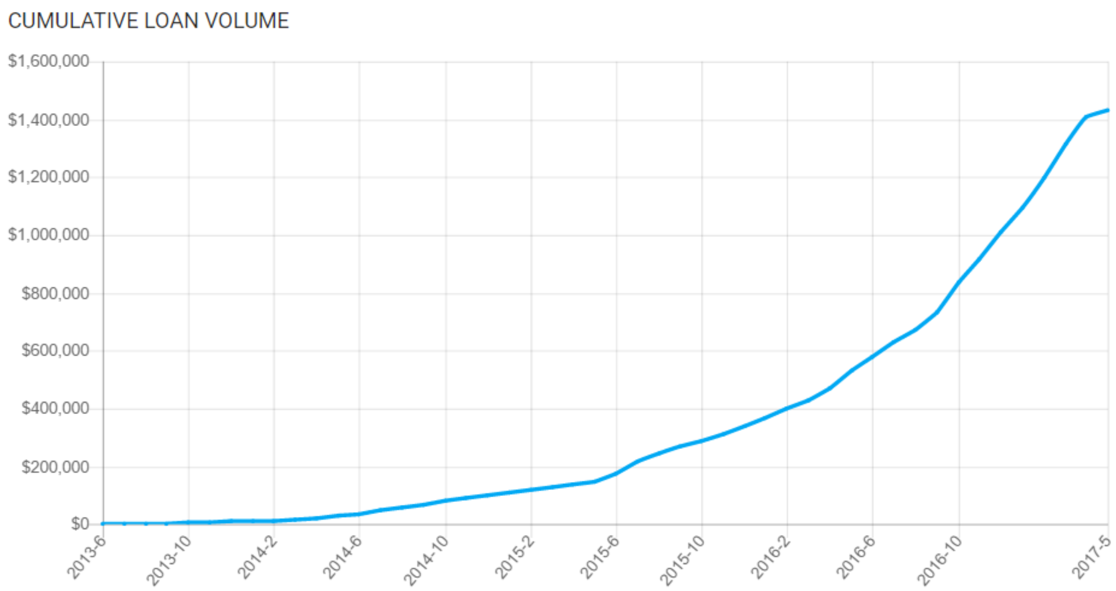
	6 weeks		6 month		12 month		36 months		60 months	
	before	after	before	after	before	after	before	after	before	after
A	7,66	n/a	7,7	n/a	7,88	13,31	8,44	n/a	n/a	n/a
B	11,15	20,93	10,29	19,07	10,69	20,30	11,66	22,61	n/a	n/a
C	14,65	24,98	13,80	22,74	14,53	24,16	15,83	26,13	16,33	26,82
D	19,94	29,82	18,06	26,57	19,47	28,25	21,08	29,57	20,71	29,10
E	27,92	36,19	24,58	31,41	22,64	32,59	24,57	31,74	22,53	30,06
F	40,48	44,17	n/a	36,77	n/a	37,19	n/a	n/a	n/a	n/a

Table 2. Loan purpose description.

- Each loan is assigned to one of the following seven standard loan purposes by the borrower:
- Eduction: Fees for apprenticeship, master craftsman, college or other higher education degree, school, PhD, continuing education and training
- Renovation: Costs for renovation of a house or apartment, car or other fixed asset repairs
- Consumption: Costs for holidays/travel, television or other purchases, relocation, medical treatment, wedding, furniture, leisure activities
- Refinancing: Refinancing of overdrafts, credit cards or other existing loans, bridge loan for business purposes
- Investment: Purchase of long-term assets (cars, machines, office equipment, real estate etc.)
- Working capital: Funds for supplies, construction material, finished and unfinished goods and other commodities
- Other: Checked if none of the above applies (e.g. tax payments)

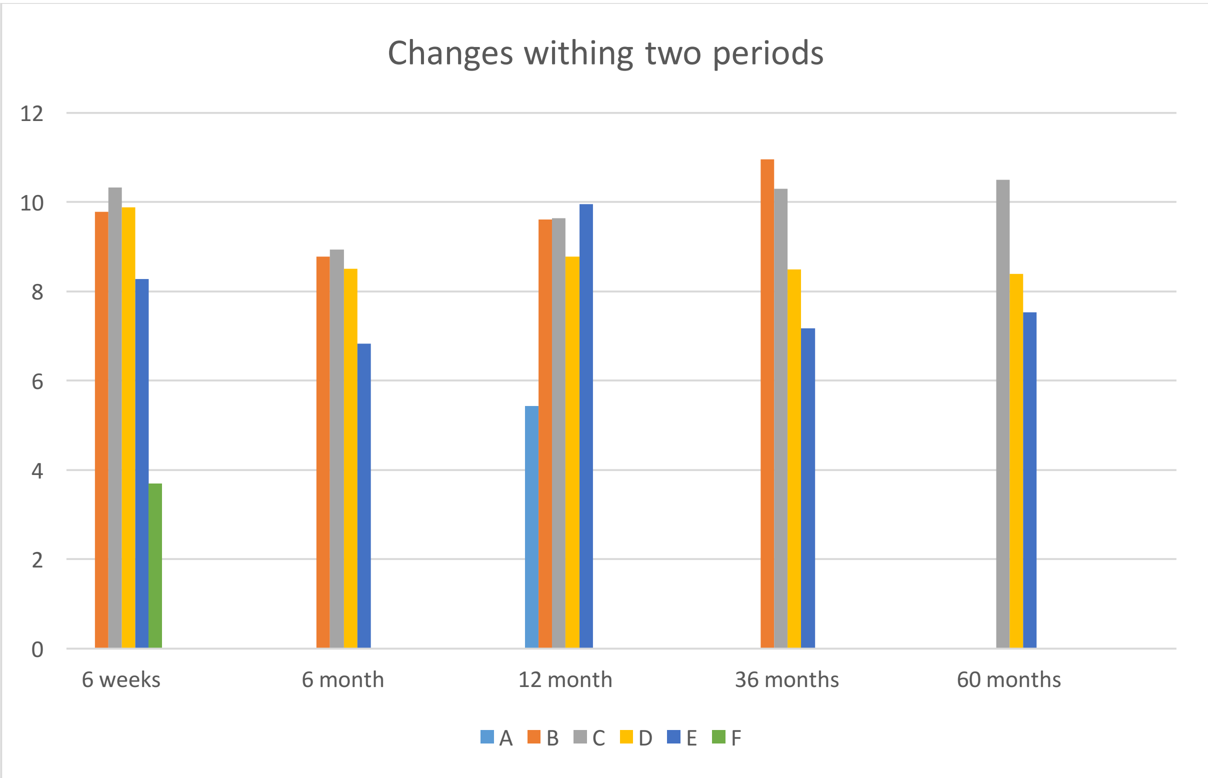
Resource: bitbond.com

Figure 1. Loan amount outstanding 2013-2017



Resource: blockchain.info

Figure 2. Interest rate change after 2015 09 28



APPENDIX C

Table 1. Pearson's correlation for continuous variables, sample period 1

Correlation	APR	GRADE	LOAN AMOUNT	ANNUAL INCOME	DESCPRITION CHARACTERS	TOTAL IDENTIFICATIONS	LOAN AMOUNT TO ANNUAL INCOME
APR	1.000000						
GRADE	0.960044	1.000000					
LOAN_AMOUNT	-0.095584	-0.130338	1.000000				
ANNUAL_INCOME	-0.186385	-0.189321	0.185261	1.000000			
DESCPRITION_CHARACTERS	-0.077989	-0.082782	-0.121022	-0.027937	1.000000		
TOTAL_IDENTIFICATIONS	-0.023152	-0.016725	-0.395625	-0.180573	0.054915	1.000000	
LOAN_AMOUNT_TO_ANNUAL_INCOME	0.236556	0.237466	-0.016531	-0.358675	0.005690	0.071529	1.000000

Table 2. Pearson's correlation for continuous variables, sample period 2

Correlation	APR	GRADE	LOAN AMOUNT	ANNUAL INCOME	DESCPRITION CHARACTERS	TOTAL IDENTIFICATIONS	LOAN AMOUNT TO ANNUAL INCOME
APR	1.000000						
GRADE	0.938823	1.000000					
LOAN_AMOUNT	0.222700	0.251615	1.000000				
ANNUAL_INCOME	-0.247854	-0.292078	0.112543	1.000000			
DESCPRITION_CHARACTERS	-0.132899	-0.074799	-0.020242	0.100788	1.000000		
TOTAL_IDENTIFICATIONS	-0.133243	-0.112871	-0.109917	-0.005580	0.025531	1.000000	
LOAN_AMOUNT_TO_ANNUAL_INCOME	0.157903	0.179132	-0.023008	-0.313300	-0.029955	-0.008486	1.000000

Table 3. Point-biseral correlation for discrete variables, sample period 1

Correlations	GRADE	APR	CONSUMPTION	EDUCATION	INVESTMENT	REFINANCING	RENOVATION	WORKING CAPITAL	OTHER	RETIRED	SALARIED	SELF EMPLOYED	STUDYING	UNEMPLOYED	DEVELOPED	DEVELOPING	IN_TRANSITION	6 WEEKS	6 MONTHS	12 MONTHS	36 MONTHS	60 MONTHS	BTC	USD
GRADE	1,00																							
APR	0,96	1,00																						
CONSUMPTION	-0,03	-0,02	1,00																					
EDUCATION	0,00	0,02	-0,03	1,00																				
INVESTMENT	-0,02	-0,02	-0,10	-0,17	1,00																			
REFINANCING	0,00	0,00	-0,02	-0,03	-0,13	1,00																		
RENOVATION	-0,08	-0,07	-0,01	-0,02	-0,09	-0,02	1,00																	
WORKING_CAPITAL	-0,09	-0,10	-0,07	-0,11	-0,42	-0,08	-0,06	1,00																
OTHER	0,13	0,13	-0,08	-0,14	-0,53	-0,10	-0,08	-0,34	1,00															
RETIRED	0,05	0,04	-0,01	0,17	-0,01	-0,02	-0,01	0,01	-0,05	1,00														
SALARIED	-0,28	-0,28	0,07	-0,07	0,07	0,03	0,01	0,06	-0,13	-0,16	1,00													
SELF_EMPLOYED	0,17	0,17	-0,05	-0,02	-0,06	-0,03	0,02	-0,04	0,13	-0,07	-0,79	1,00												
STUDYING	0,14	0,13	-0,03	0,12	-0,09	-0,04	-0,03	-0,03	0,09	-0,03	-0,32	-0,13	1,00											
UNEMPLOYED	0,15	0,16	-0,02	-0,01	0,07	0,05	-0,02	-0,02	-0,06	-0,02	-0,25	-0,11	-0,04	1,00										
DEVELOPED	-0,30	-0,30	-0,01	0,03	0,02	-0,01	0,06	-0,06	0,02	0,02	-0,04	-0,01	0,08	0,03	1,00									
DEVELOPING	0,28	0,28	0,02	-0,04	-0,01	0,00	-0,06	0,07	-0,02	-0,01	0,04	0,01	-0,07	-0,03	-0,97	1,00								
IN_TRANSITION	0,08	0,08	-0,01	0,02	-0,01	0,04	-0,01	-0,04	0,03	-0,01	0,02	0,00	-0,03	-0,02	-0,14	-0,09	1,00							
_6_WEEKS	0,00	0,11	-0,01	-0,04	-0,07	0,02	-0,06	-0,10	0,18	0,01	-0,04	0,07	-0,04	-0,02	0,07	-0,06	-0,05	1,00						
_6_MONTHS	0,00	-0,12	0,04	0,03	0,02	0,00	0,05	0,06	-0,11	0,00	0,03	-0,04	0,03	-0,02	-0,02	0,01	0,02	-0,77	1,00					
_12_MONTHS	0,00	-0,01	-0,04	0,03	0,05	-0,02	-0,04	0,08	-0,11	0,00	0,03	-0,05	0,02	0,03	-0,07	0,07	0,00	-0,39	-0,18	1,00				
_36_MONTHS	-0,03	0,00	-0,02	-0,03	0,05	-0,02	0,12	0,01	-0,07	-0,02	0,00	-0,02	0,01	0,06	-0,02	0,00	0,06	-0,17	-0,08	-0,04	1,00			
_60_MONTHS	0,02	0,03	-0,01	-0,02	0,02	-0,02	-0,01	-0,03	0,02	-0,01	-0,03	0,04	0,02	-0,02	-0,04	0,02	0,08	-0,13	-0,06	-0,03	-0,01	1,00		
BTC	0,03	0,03	-0,09	-0,13	0,01	-0,04	-0,04	-0,07	0,16	-0,14	0,01	0,02	0,05	-0,04	0,16	-0,14	-0,07	0,16	-0,10	-0,11	0,00	-0,04	1,00	
USD	-0,03	-0,03	0,09	0,13	-0,01	0,04	0,04	0,07	-0,16	0,14	-0,01	-0,02	-0,05	0,04	-0,16	0,14	0,07	-0,16	0,10	0,11	0,00	0,04	-1,00	1,00

Table 4. Point-biseral correlation for discrete variables, sample period 2

Correlations	GRADE	APR	CONSUMPTION	EDUCATION	INVESTMENT	REFINANCING	RENOVATION	WORKING CAPITAL	OTHER	RETIRED	SALARIED	SELF EMPLOYED	STUDYING	UNEMPLOYED	DEVELOPED	DEVELOPING	IN_TRANSITION	6 WEEKS	6 MONTHS	12 MONTHS	36 MONTHS	60 MONTHS	BTC	USD
GRADE	1,00																							
APR	0,94	1,00																						
CONSUMPTION	0,11	0,10	1,00																					
EDUCATION	0,08	0,07	-0,04	1,00																				
INVESTMENT	0,14	0,14	-0,13	-0,16	1,00																			
REFINANCING	0,00	-0,02	-0,05	-0,06	-0,20	1,00																		
RENOVATION	-0,03	-0,02	-0,04	-0,04	-0,13	-0,05	1,00																	
WORKING_CAPITAL	-0,21	-0,22	-0,14	-0,16	-0,51	-0,20	-0,14	1,00																
OTHER	0,00	0,04	-0,08	-0,09	-0,28	-0,11	-0,08	-0,29	1,00															
RETIRED	0,07	0,05	0,23	0,08	-0,06	-0,03	-0,02	-0,02	-0,04	1,00														
SALARIED	0,03	0,04	-0,01	0,08	0,15	0,15	0,10	-0,26	-0,06	-0,12	1,00													
SELF_EMPLOYED	-0,06	-0,07	-0,02	-0,12	-0,14	-0,14	-0,09	0,27	0,06	-0,07	-0,94	1,00												
STUDYING	0,07	0,07	-0,02	0,07	0,01	-0,03	-0,02	-0,07	0,08	-0,01	-0,13	-0,07	1,00											
UNEMPLOYED	0,05	0,02	-0,02	0,07	-0,03	-0,03	-0,02	0,06	-0,04	-0,01	-0,13	-0,07	-0,01	1,00										
DEVELOPED	-0,37	-0,32	-0,07	0,00	-0,16	0,01	0,04	0,17	0,01	-0,05	-0,02	0,01	0,05	0,05	1,00									
DEVELOPING	0,34	0,28	0,04	0,01	0,17	0,01	-0,03	-0,16	-0,02	0,06	0,03	-0,02	-0,05	-0,05	-0,96	1,00								
IN_TRANSITION	0,11	0,12	0,12	-0,03	-0,02	-0,04	-0,03	-0,02	0,06	-0,01	-0,02	0,03	-0,02	-0,02	-0,16	-0,13	1,00							
_6_WEEKS	0,05	0,31	-0,01	0,01	0,03	-0,06	0,06	-0,12	0,15	-0,06	0,10	-0,08	0,02	-0,07	0,15	-0,16	0,04	1,00						
_6_MONTHS	0,08	-0,18	0,02	0,00	-0,04	0,05	-0,04	0,04	-0,02	-0,03	0,01	-0,01	0,04	0,00	-0,06	0,06	0,01	-0,57	1,00					
_12_MONTHS	-0,13	-0,14	0,01	-0,05	0,01	-0,02	-0,02	0,09	-0,10	0,12	-0,09	0,07	-0,05	0,04	-0,06	0,09	-0,08	-0,36	-0,44	1,00				
_36_MONTHS	-0,04	0,00	-0,03	0,07	-0,03	0,04	0,03	0,01	-0,04	-0,02	0,02	-0,01	-0,02	-0,02	-0,02	0,00	0,05	-0,13	-0,15	-0,10	1,00			
_60_MONTHS	-0,01	0,01	-0,03	0,03	0,05	0,02	-0,03	-0,01	-0,06	-0,01	-0,13	0,11	-0,01	0,13	-0,07	0,08	-0,02	-0,10	-0,12	-0,08	-0,03	1,00		
BTC	0,04	0,03	-0,09	-0,06	0,31	-0,10	-0,06	-0,24	0,10	-0,02	0,15	-0,14	0,01	-0,07	-0,15	0,14	0,04	0,01	0,01	-0,03	-0,01	0,02	1,00	
USD	-0,04	-0,03	0,09	0,06	-0,31	0,10	0,06	0,24	-0,10	0,02	-0,15	0,14	-0,01	0,07	0,15	-0,14	-0,04	-0,01	-0,01	0,03	0,01	-0,02	-1,00	1,00

APPENDIX D

Table 1. Logistic regression with BTC as dummy for sample from 28/12/2014

Dependent Variable: LOAN_STATUS
Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)
Date: 05/20/17 Time: 14:30
Sample: 1 467
Included observations: 458
Convergence achieved after 3 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.546296	1.557725	-0.350701	0.7258
GRADE	0.401177	0.136992	2.928481	0.0034
LOAN_TERM	0.971825	0.152383	6.377514	0.0000
USD_PRINCIPAL_OUTSTANDIN	-0.000222	9.96E-05	-2.232402	0.0256
DESCPRITION_CHARACTERS	0.000550	0.000426	1.292476	0.1962
OTHER	0.196253	0.851914	0.230367	0.8178
INVESTMENT	-0.261346	0.836755	-0.312332	0.7548
REFINANCING	-0.380434	1.032586	-0.368429	0.7126
EDUCATION	0.664699	1.088604	0.610598	0.5415
WORKING_CAPITAL	0.573850	0.856410	0.670064	0.5028
ANNUAL_INCOME_USD	9.04E-07	4.39E-06	0.206104	0.8367
TOTAL_IDENTIFICATIONS	-0.019351	0.052115	-0.371307	0.7104
DEVELOPED	-1.812696	0.900494	-2.013003	0.0441
DEVELOPING	-1.330396	0.890566	-1.493877	0.1352
SALARIED	-0.304299	0.617677	-0.492650	0.6223
SELF_EMPLOYED	-0.263772	0.630734	-0.418198	0.6758
UNEMPLOYED	-0.558432	0.842133	-0.663116	0.5073
FINANCIAL_SERVICES	-0.845904	0.569943	-1.484190	0.1378
INFORMATION_AND_COM	-0.637610	0.438263	-1.454856	0.1457
PROFESSIONAL_AND_SCIENTI	-0.465674	0.468764	-0.993409	0.3205
MANUFACTURING	-1.016505	0.588832	-1.726306	0.0843
EDUCATION01	-1.299404	0.912580	-1.423880	0.1545
OTHER_SERVICES	-0.279566	0.463229	-0.603516	0.5462
WHOLESALE_AND_RETAIL	-0.257801	0.566844	-0.454801	0.6493
PUBLIC_AND_DEFENCE	0.326759	0.724036	0.451302	0.6518
HUMAN_HEALTH	0.117110	0.631073	0.185573	0.8528
TRANSPORTATION	-0.337627	1.062179	-0.317863	0.7506
ADMIN_AND_SUPPORT	0.490851	0.664395	0.738795	0.4600
AGRICULTURE	-1.103898	0.951574	-1.160075	0.2460
ELECTRICITY	0.297038	0.655279	0.453300	0.6503
LOAN_AMOUNT_TO_ANNUAL_IN	-0.081206	0.098083	-0.827932	0.4077

McFadden R-squared	0.181911	Mean dependent var	0.449782
S.D. dependent var	0.498016	S.E. of regression	0.452328
Akaike info criterion	1.261217	Sum squared resid	87.36461
Schwarz criterion	1.540547	Log likelihood	-257.8187
Hannan-Quinn criter.	1.371231	Deviance	515.6375
Restr. deviance	630.2949	Restr. log likelihood	-315.1475
LR statistic	114.6575	Avg. log likelihood	-0.562923
Prob(LR statistic)	0.000000		

Obs with Dep=0	252	Total obs	458
Obs with Dep=1	206		

Table 2. Logistic regression for USD as dummy for sample from 28/12/2014

Dependent Variable: LOAN_STATUS
Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)
Date: 05/20/17 Time: 14:35
Sample: 1 560
Included observations: 552
Convergence achieved after 3 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-2.249917	1.121751	-2.005719	0.0449
GRADE	0.287032	0.116159	2.471033	0.0135
LOAN_TERM	0.939329	0.129743	7.239904	0.0000
USD_PRINCIPAL_OUTSTANDIN	-0.000198	7.10E-05	-2.781931	0.0054
DESCPRITION_CHARACTERS	-0.000832	0.000354	-2.350356	0.0188
OTHER	0.111817	0.428755	0.260795	0.7943
INVESTMENT	-0.138108	0.387897	-0.356044	0.7218
REFINANCING	0.292303	0.496796	0.588376	0.5563
EDUCATION	0.194223	0.500185	0.388303	0.6978
WORKING_CAPITAL	0.654444	0.385385	1.698157	0.0895
ANNUAL_INCOME_USD	2.82E-06	4.46E-06	0.631567	0.5277
TOTAL_IDENTIFICATIONS	-0.087685	0.049091	-1.786169	0.0741
DEVELOPED	0.634186	0.705359	0.899096	0.3686
DEVELOPING	0.481459	0.692950	0.694796	0.4872
SALARIED	0.251290	0.516622	0.486409	0.6267
SELF_EMPLOYED	0.096901	0.540227	0.179370	0.8576
UNEMPLOYED	-0.754242	0.800722	-0.941953	0.3462
FINANCIAL_SERVICES	-0.627392	0.450505	-1.392643	0.1637
INFORMATION_AND_COM	-0.463768	0.370951	-1.250213	0.2112
PROFESSIONAL_AND_SCIENTI	-0.526927	0.408825	-1.288879	0.1974
MANUFACTURING	-0.003373	0.490372	-0.006879	0.9945
EDUCATION01	-0.613303	0.595518	-1.029863	0.3031
OTHER_SERVICES	-0.397128	0.400634	-0.991247	0.3216
WHOLESALE_AND_RETAIL	-0.099614	0.398327	-0.250080	0.8025
PUBLIC_AND_DEFENCE	-0.466466	0.614995	-0.758488	0.4482
HUMAN_HEALTH	-0.677654	0.571042	-1.186698	0.2353
TRANSPORTATION	0.307561	0.747263	0.411583	0.6806
ADMIN_AND_SUPPORT	-0.380973	0.558106	-0.682618	0.4948
AGRICULTURE	-0.909150	0.772652	-1.176662	0.2393
ELECTRICITY	0.405192	0.974566	0.415767	0.6776
LOAN_AMOUNT_TO_ANNUAL_IN	0.123330	0.163474	0.754433	0.4506

McFadden R-squared	0.126132	Mean dependent var	0.445652
S.D. dependent var	0.497488	S.E. of regression	0.469803
Akaike info criterion	1.313413	Sum squared resid	114.9924
Schwarz criterion	1.555659	Log likelihood	-331.5019
Hannan-Quinn criter.	1.408063	Deviance	663.0038
Restr. deviance	758.6998	Restr. log likelihood	-379.3499
LR statistic	95.69609	Avg. log likelihood	-0.600547
Prob(LR statistic)	0.000000		

Obs with Dep=0	306	Total obs	552
Obs with Dep=1	246		