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Portfolio optimization for an P2P investor on Zonky

Bachelor's Thesis

Author of the Thesis: Filip Jonáš

Study programme: Economics and finance

Supervisor: Mgr. Petr Polák, MSc.

Year of the defence: 2019

Declaration

1. I hereby declare that I have compiled this thesis using the listed literature and resources only.
2. I hereby declare that my thesis has not been used to gain any other academic title.
3. I fully agree to my work being used for study and scientific purposes.

In Prague on Filip Jonáš

10.5.2019

References

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Abstract

This thesis analyzes the Czech peer-to-peer lending platform Zonky. The goal was to find the optimal portfolio for a risk-averse investor investing in Zonky loans. For this purpose, the Modern portfolio theory from Markowitz was used. Based on the provided loan book containing information about loans which Zonky has provided since its foundation we examined the statistical properties of the individual risk categories represented by the interest rate charged. The optimization was done using the Excel Solver tool assuming that the loan categories are uncorrelated as well as considering the correlation we found using the variance-covariance matrix. For both cases, the portfolio minimizing the standard deviation as well as the portfolio which maximizes the Sharpe ratio was found. Generally, both types of portfolios were comprised mainly of loans with lower interest rate. According to our results, it seems that such loans offer better relationship between risk and return compared to categories which are riskier. Also, we showed that the platform's recovery rate has a significant impact on the performance of the loan categories especially of those which are among the riskiest. Furthermore, we demonstrated that the correlation between individual risk categories should not be ignored when a portfolio analysis is done.

Abstrakt

Tato práce se zabývá analýzou české peer-to-peer platformy Zonky, která zprostředkovává půjčky mezi lidmi. Jejím cílem bylo nalézt optimální portfolio pro rizikově averzního investora. K tomuto účelu byla použita Moderní teorie portfolia. Na základě dat o půjčkách, které Zonky poskytlo od svého založení, byla provedena analýza jednotlivých kategorií půjček, přičemž každá kategorie zahrnovala půjčky se stejným úrokem. Samotná optimalizace byla provedena v programu Excel pomocí doplňku Řešitel. Nejdříve za předpokladu, že jednotlivé kategorie jsou nekorelované, a následně za použití korelací získaných z kovarianční matice. Pro oba případy bylo určeno portfolio s minimální směrodatnou odchylkou a portfolio, pro které je Sharpův poměrový koeficient maximální. Oba typy portfolia se obecně skládaly především z méně rizikových kategorií. Z výsledků vyplývá, že půjčky s menším úrokem nabízí lepší poměr mezi rizikem a výnosem. Dále je ukázáno, že míra zpětného

získání zbývajícího dluhu u půjček se selháním hraje významnou roli při určování výkonnosti jednotlivých rizikových kategorií půjček, především pak pro rizikovější kategorie. Kromě toho jsme demonstrovali, že by korelace mezi jednotlivými kategoriemi neměla být při analýzách portfolia zanedbávána.

Keywords:
Markowitz, Modern portfolio theory, covariance matrix, P2P lending, Zonky, diversification

Klíčová slova:
Markowitz, Moderní teorie portfolia, kovarianční matice, P2P půjčky, Zonky, diverzifikace

Název práce:

Optimalizace portfolia investora na Zonky

Acknowledgment
I wish to express gratitude to the thesis supervisor Mgr. Petr Polák, MSc. for useful advices. Also, I would like to thank to Vít Fincl and Jan Tročil for providing me with the necessary information and data which are not publicly accessible. Besides that I am grateful to my family for supporting me during my studies.

Bachelor thesis proposal

Author: Filip Jonáš

Supervisor: Mgr. Petr Polák, MSc.

Title: Portfolio optimization for an P2P investor on Zonky

Research question and motivation:

Sharing economy is experiencing a big boom. One of the new trends is so called peer-to-peer lending. It is a way how to lend and borrow money without use of a financial institution's services. In practice the matching process is done by P2P online companies. It started in 2005 in the UK when the first P2P lending company, called Zopa, launched. Several years later this phenomenon arrived in the Czech Republic. Currently the leading P2P company in the Czech Republic is called Zonky, which launched in 2015.

P2P might be a good alternative way for investors how to invest their money as they earn money from the interest rate paid by the borrowers. However, this platform is also attractive for many borrowers as well. The reason why some borrowers may prefer P2P lending to getting a loan from a traditional bank institution is that their poor credit history would make them pay high interest rate in the case of the bank loan or their loan application would even be rejected. However, the risk that these private money providers are facing is that these, in some cases less reliable, debtors will not repay the money. Every loan applicant is therefore put into one of the several risk categories which reflects the risk.

The lender based on his preferences, especially his expected return, can choose the loans to invest in. The question which arises is how should the lender allocate his funds to reach his desired expected return while facing the lowest possible risk.

Contribution:

I would like to find the optimal portfolio for a risk averse investor who invests his money in loans on the Czech platform Zonky whose goal is to maximize his returns and minimize the risk associated with lending the money.

Number of studies have been conducted focusing on P2P business. Most of them dealt with the behavior of the parties involved and risk assessment of individual loans based on characteristics of borrowers. Not many of them focused on the portfolio, consisting of these individual loans. Primarily the biggest companies as for instance the Lending club, Prosper from the USA or Chinese providers have been examined. Only few studies were concerned with the relatively small P2P market in the Czech Republic represented by Zonky, as the leading company in this country. Only Bock,Tichý (2017), however, were concerned with portfolio optimization for Zonky. This study used modified Markowitz portfolio theory, not considering the correlation between risk classes. That is why the author would like to shed light on this company using classical Markowitz approach (Markowitz (1952)) for finding the optimal portfolio.

The goal of this thesis is to show the usefulness of the modern portfolio theory also in P2P business. Put differently that it is possible to reduce the risk exposure by investing in a certain way, compared for instance to the case of investing equal share to each risk category.

Methodology:

Historical data about loans on Zonky will be analyzed. Author will use the Markowitz modern portfolio theory which says that thanks to diversification it is possible to find an optimal portfolio minimizing the risk as long as the assets being analyzed are not perfectly correlated. A study from 2017 proved Markowitz theory to be useful for portfolio optimization using data from the US P2P company Lending club. Therefore, the goal will be to use statistical tools to find a variance- covariance matrix and correlation between loans risk groups, which constitute a P2P portfolio of an investor. The task will be to do optimization based on given conditions using EXCEL/ VBA.

Literature review:

Lee, E., & Lee, B. (2012). Herding behavior in online P2P lending: An empirical investigation. Electronic Commerce Research and Applications, 11(5), 495-503.

Puro, Lauri; Teich, Jeffrey E.; Wallenius, Hannele; Wallenius, Jyrki. (2009). Borrower Decision Aid for people-to-people lending. Aalto University School of Science and Technology, New Mexico State University, Aalto University School of Economics.

Berger, S. C., & Gleisner, F. (2009). Emergence of financial intermediaries in electronic markets: The case of online P2P lending. BuR-Business Research, 2(1), 39-65. v

Claessens, Frost, Turner, Zhu (2018) Fintech credit markets around the world: size, drivers and policy issues, BIS Quarterly Review

Markowitz, H. (1952). Portfolio selection. The journal of finance, 7(1), 77-91

Sharpe, W. F. (1963). A simplified model for portfolio analysis. Management science, 9(2), 277-293

Abbreviations

CNB - Czech national bank

P2P - peer-to-peer

CZK - Czech crown

MPT - Modern portfolio theory

RFA – risk-free asset

US – the United States

GB – the Great Britain

CZK – the Czech crown

ROI - return on investment

RV - random variable(s)

PWC - PricewaterhouseCoopers

CINBR - The Client Information Non-Bank Register

CIBR - Client Information Bank Register

CR – The Czech Republic

CAPM - Capital Asset Pricing Model

VCM - variance-covariance matrix

SR - Sharpe ratio

CAL - Capital allocation line

VBA – Visual Basic for Applications

RR – recovery rate

RMB - Renminbi

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Warning:

This is an academic study. Author does not recommend using it as an investing guide as it is based on simplifying assumptions due to limited access to data. Any conclusion drawn from this study is subject to the validity of these assumptions.

Introduction

Sharing economy has become quite popular in the last few years. It is based on sharing or renting of goods or services using an IT system. The ownership of these assets is not transferred between the members of this economy and the period of usage is usually short. This kind of economy is associated with higher efficiency, lower transaction costs, reduced information asymmetry and higher competition in the whole market. Nowadays the sharing economy can be found in different sectors such as food, mobility, tourism or financial services. link Example of platforms engaging in this kind of business is Uber, allowing each car owner to become a taxi driver or Airbnb which makes it possible for any owner of a house or an apartment to rent it to another person for a couple of days. What do such companies usually have in common is the use of some kind of innovative IT system. That is why the sharing economy is closely linked with the term fintech (financial technology). It is a new financial industry that applies technology to improve the use and delivery of financial services[1]. Its goal is to compete with the traditional way of providing the financial services and generally to make it easier for general public to use the services. Examples of implementing this technology is the development of user-friendly applications for electronic devices such as smartphones or creating online platforms.

The peer-to-peer lending meets both criteria. It can be described as a way of providing and obtaining of financial funds without a use of traditional financial institutions which stand traditionally between those who had an excess of available funds and those who wished to obtain those extra funds. The first company in this area was Zopa, founded in 2005, situated in the United Kingdom[2] This implies that P2P is a relatively new financial sector. In the Czech Republic the leading company is a company called Zonky.

The previous research was primarily concerned with the credit risk with this kind of business and behavior of the parties involved in P2P lending. In this thesis the author will focus on finding the optimal portfolio for an investor lending his money through the Czech P2P

[1] Fintech, Investopedia, https://www.investopedia.com/terms/f/fintech.asp
[2] Source: https://www.zopa.com/about

platform Zonky. The data of this company will be analyzed. First, the P2P lending will be described including the main characteristics, advantages as well as disadvantages. market and the Czech company itself

After that light will be shed on the theory behind finding the optimal portfolio. In this thesis we will use the Modern portfolio theory for the analysis of data from Zonky. This theory is usually used for analyzing stocks but proved to be useful also for analyzing P2P loans. The author will try to adjust the loan data in best possible way to make the theory applicable. The goal of this thesis is to answer the question what is the best way for an investor to allocate his funds into individual loans categories. Such results might be certainly helpful for an investor who wish to reach certain expected return while facing as little risk as possible. Especially with respect to the fact, that Zonky offers no so-called auto-investing tool which invests money automatically based on investor's preferences.

This thesis consists of 6 chapters. First, a general overview about P2P market is given. This includes the advantages as well the advantages of this kind of lending. Also, the historical development of P2P lending including the predictions about possible future development is mentioned. In the third chapter, the summary of literature is given. The fourth chapter introduces the statistical measures used in the optimization. In the empirical part statistical properties of the loans provided on Zonky are shown, which is the basis for the portfolio analysis. The last chapter shows the result.

1. P2P lending – theoretical background

1.1 P2P lending

Traditionally, banking institutions played crucial role in financial market by taking deposits from public and making loans to individuals, businesses and government.

The following idea is behind the peer-to-peer lending. People can borrow and lend money to each other directly through an intermediator without the use of a traditional banking institution. During the past few years P2P lending has experienced high growth and some studies shows that the growth will continue. USA, China and UK are among the countries where the activity of P2P business has been high. For lenders P2P loans can represent an interest investment opportunity. For borrowers, P2P loan might offer better conditions compared to the traditional loan. Both investors and debtors benefit from the use of innovative technology and generally smooth lending process which characterizes P2P lending. As Greiner and Wang (2009) points out, the goal of borrowers is to find the best investment opportunities. On the other hand, investors try to achieve the highest profit while facing a certain level of risk. The role of the intermediator, mostly represented by an online platform, is to match lenders with borrowers, verify the identity of both parties to avoid potential frauds, assess the level of risk to individual borrowers which are usually put into one of the predefined risk categories based on their characteristics (such as income, FICO score, age, number of children), as well as to collect payments. The risk categories are usually represented by interest rate charged on the loan. Therefore, the higher the risk of borrower's default the higher interest he should be applied. If the borrower defaults on his debt obligations the platform should try to collect as much from the remaining debt as possible. For these kinds of services usually a fee is charged (Galloway, 2009).

Compared to the traditional model of banking loans, in the case of P2P lending, both sides are represented by individuals or companies. Milne and Parbooteeah (2016) argue that the "peer-to-peer" nature of this kind of lending is not as important as it is for instance in platforms such as Airbnb or Uber as there is no personal relationship between borrowers and lenders due to diversification.

One of the main characteristics of P2P platforms is that they are able to match borrowers and lenders without any interest margin. The reason for that is the fact that the platforms do not hold any of the loans themselves but they lend (Milne & Parboteeah, 2016). Tang (2019) finds that P2P lending is a substitute for bank lending with regards to serving infra-marginal bank borrowers. At the same time, it complements bank loans in case of small loans.

In P2P business there are several borrower segments. Consumer loans are typically used for weddings, medical expenses or debt consolidation. Zopa, Zonky or Lending Club are the platforms engaging mainly in this type of borrowing. On the other hand, Funding Circle focuses on providing loans to small businesses. Another P2P segment is represented by student loans. Platforms which provides funds to students is the platform Commonbond, situated in the US, promising low rates and simple lending process to students who would like to obtain funds in order to fund their education. The last main borrower segment is the P2P Real Estate represented by the platform SoFi.

Significant differences among countries can be found when we compare the type of the borrower segment which prevails. In New Zealand, Germany and United States the most debtors are consumers while for instance in some Asian countries like in Japan or Singapore the most borrowers are businesses.

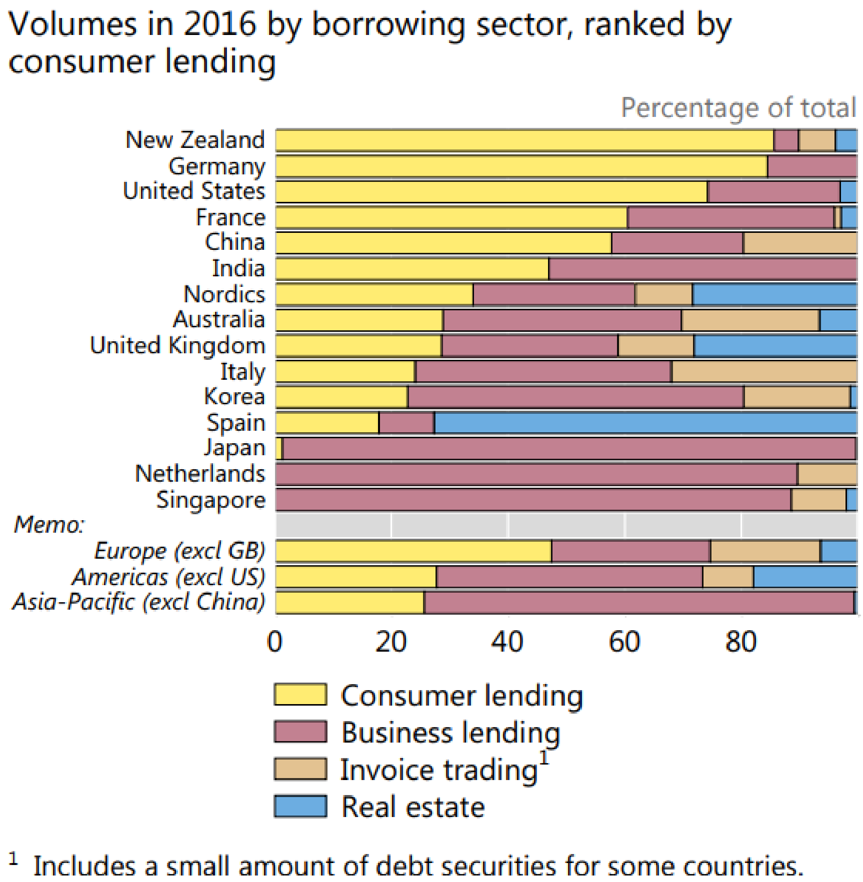

Figure 1.1: Note: exluding student loans, (Claessens, Frost, Turner, & Zhu 2018)

1.2 Growth of P2P lending

P2P lending has experienced high growth in the last few years in several countries such as the United states, China and UK thanks to the advantages it brings as discussed in other chapters. Huang (2018) identifies three key factors which are important for online P2P to grow: large number of providers of funds looking for investments offering higher returns than bank deposits, broad access to the internet and great demand for funds of small sizes. He points out that it is crucial that these three elements emerge at the same time. Another factor that is likely to have contributed to the success of P2P lending is the perception that by directly linking borrowers with lenders the P2P lending represents a more beneficial form of finance compared to the case of conventional financial intermediaries which tend to be seen as exploiters of their market power only seeking profits regardless of the interest of their customers as Milne & Parboteeah (2016) finds out.

Also as survey indicates, people generally distrust financial institutions. 2018 Edelman Trust barometer showed that globally the average share of population which trusted the financial institutions was only 48 %[3].

The Figure 1.2 shows the rapid growth of P2P business in the first years of existence.

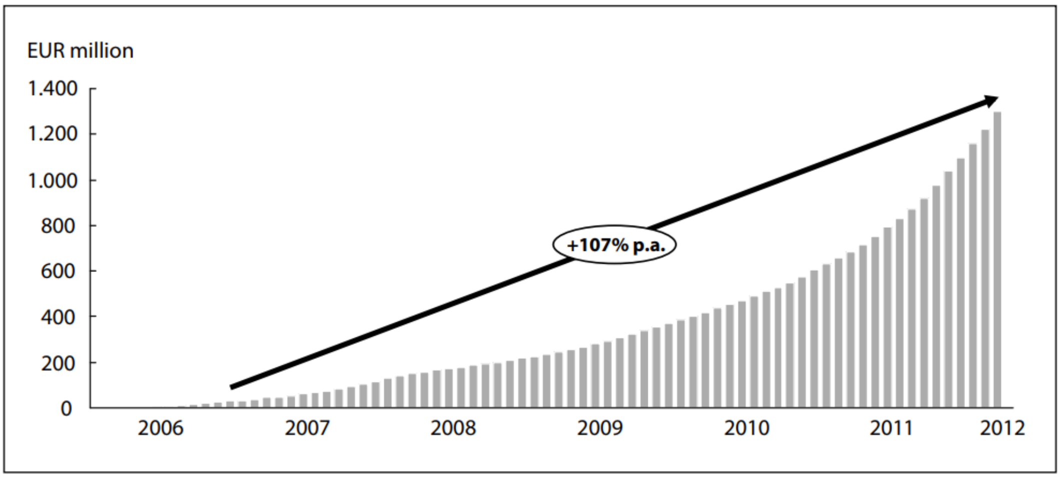

Figure 1.2: Outstanding volume of global peer-to-peer lending market, (Moenninghoff & Wieandt, 2013)

The more recent data confirms upward trend in the overall volume of P2P loans and increasing share of the Asian market. In 2016 China was by far the largest P2P market in the world followed by the United States and United Kingdom. However, data indicates a slowdown in main markets, in case of China there was even a small decrease between the years 2017 and 2018. This is partly due to the stringer regulatory policy.

[3] 2018 Edelman Trust Barometer Global report, retrieved Mai 1, 2019 from https://www.edelman.com/sites/g/files/aatuss191/files/201810/Edelman_Trust_Barometer_Financial_Services_2018.pdf

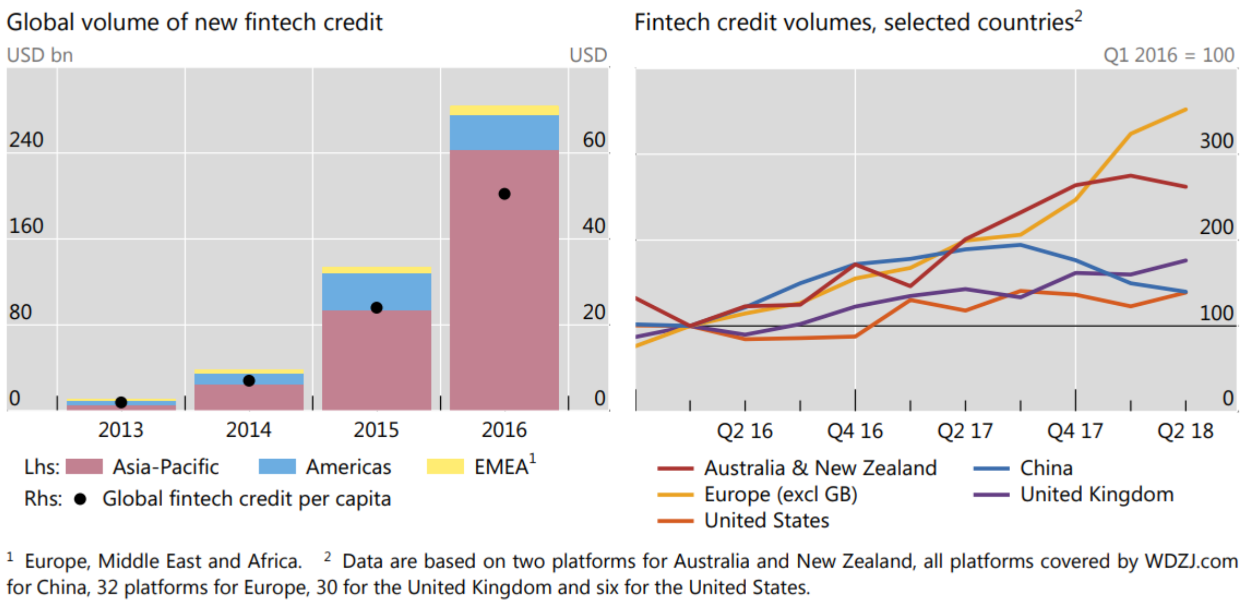

Figure 1.3: P2P volume[4],(Claessens, Frost, Turner, & Zhu 2018)

UK

P2P lending in the UK started in 2005 with the launch of Zopa[5] which was also the first P2P company worldwide It has lent more than 4 billion pounds to almost half a million borrowers and generated GBP 250 million interests. In 2015 P2P lending in total accounted for 3,2 billion GBP. Based on the data from 2015, the UK was leading market with P2P business in the EU. In 2014, only around 20 percent of the entire EU size was outside the UK. (Wardrop, Zhang, Rau, & Gray, 2015). Among the biggest segments were the consumer lending, real estate and business lending. Currently the largest P2P lending company measured by the total amount of loans outstanding (GBP 828 million[6])is Funding Circle which focuses on business lending. Namely, on providing loans to small and medium sized businesses. Since 2010 almost 50 000 UK businesses borrowed 5 billion GBP from Funding circle[7]. This company is followed by Zopa and Rate Setter. The first focusing on consumer lending while the latter also provides loan to business and real estate loans. Both Zopa and Funding Circle are members of Peer-to-peer finance association (P2PFA) which is a representative and self-regulatory body for P2P lending in the UK. It cooperates with policy-makers and regulators in order to ensure effective regulatory regime.

[4] Note: Author uses the term "fintech credit" as a synonym for P2P loan
[5] Zopa, retrieved April 20, 2019 from https://www.zopa.com/about/our-story
[6] "Company loan amounts", P2Pmoney, retrieved April 23, 2019 from http://www.p2pmoney.co.uk/statistics/size.htm
[7] Funding Circle, retrieved April 25, 2019 from https://www.fundingcircle.com/uk/

US

The P2P lending in the US started in 2006 when Prosper Marketplace was launched. It was followed by LendingClub one year later. Currently it is the biggest P2P company in the world which has issued more than 3,5 million loans worth more than $40 billion[8] since 2007. Also, it became the first publicly-traded P2P platform in the US. In 2014, it went public on the New York Stock Exchange and by May 2019 it reached market capitalization of $1,45 billion[9]. The P2P lending business grew first slowly but this changed in 2013. Mariotto (2016) suggest that Prosper's rules on accepting investors and borrowers to increase its market share. In the US, Prosper Marketplace and Lending Club and Funding Circle currently belong to the leaders in this field. In 2014, LendingClub and Prosper Marketplace had a 98% market share[10]. The P2P business also experienced rapid growth. The US marketplace loan origination doubled every year between 2010 and 2014[11].

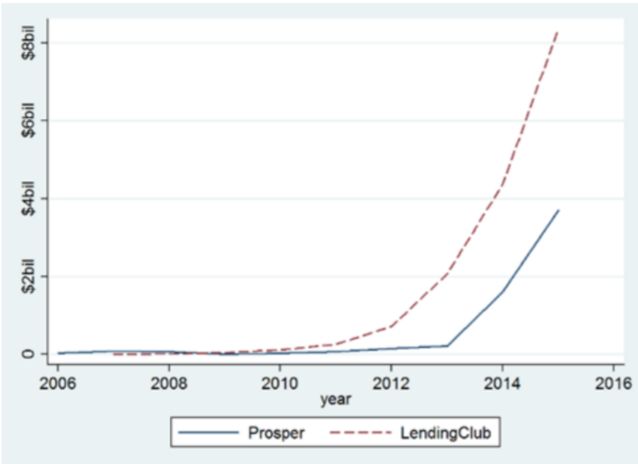

Figure 1.4: growth of Prosper and LendingClub, Mariotto (2016)

China

In China P2P lending business started in 2007 when the first platform was created - Ppdai.com[12]. According to Huang (2018), P2P lending has experienced a period of massive growth especially after 2013 when the internet finance became a general policy tool of Chinese government for stimulating the slowing economy. In 2015, the number of platforms

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[8] LendingClub, retrieved April 24, 2019 from https://www.lendingclub.com/info/statistics.action

[9] "LendingClub Market Cap 2008-2018", Macrotrends, retrieved April 24, 2019 from https://www.macrotrends.net/stocks/charts/LC/lendingclub/market-cap

[10] "Banking without banks", The Economist, retrieved April 24, 2019 from https://www.economist.com/finance-and-economics/2014/02/28/banking-without-banks

[11] "Can P2P lending reinvent banking?", Morgan Stanley, retrieved April 25, 2019 from http://www.morganstanley.com/ideas/p2p-marketplace-lending

[12] Ppdai.com, retrieved April 25, 2019 from http://ir.ppdai.com/

grew by 40 %. One year later this number shrunk to 10% caused by stricter regulations. In 2017 there were more than 2300 P2P platforms while the trading volume 2 years earlier reached $67 billion which was more than four times the volume in the UK. He identifies three main reasons for that: high popularity of internet, large supply of funds and unmet financial needs. However, due to the recent strict regulations the market in China is likely to shrink significantly as mentioned in the part of the chapter dealing with regulation.

1.2.1 Future of the P2P lending

Several studies predict that the current growth of P2P lending sector will continue. PWC suggests that by 2025 P2P lending might represent 10 percent of the whole US market for revolving consumer debt which will account for approximately $800 billion[13]. Moldow (2015) expects the global P2P lending business to grow to 1 trillion USD by 2025, assuming it will capture 10 percent of consumer and other lending markets. Another study, conducted in 2015, predicts the P2P lending to capture 10 percent of the US lending market by 2020 and to reach a stock of 150-490 billion USD globally[14]. Transparency Market research expects the P2P market to grow from 26 billion USD in 2015 to almost 900 billion USD by 2024[15].

1.3 Advantages of P2P lending

The rapid growth of P2P lending could have several reasons which are linked to the advantages of P2P loans compared to the traditional bank loans. P2P loan might represent a source of funds which is accessible for borrowers under more favorable conditions compared to the bank loan. Also, P2P platforms can provide funds to some applicants whose application would have been declined by traditional lenders. According to a survey, 21 percent of borrowers of Funding circle, currently one of the leading providers in the UK, believe that they would not have been able to access finance through a bank[16].

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[13] "Peer pressure", PWC, retrieved April 10, 2019 from https://www.pwc.com/us/en/consumer-finance/publications/assets/peer-to-peer-lending.pdf

[14] "Can P2P lending reinvent banking?", Morgan Stanley, retrieved April 25, 2019 from http://www.morganstanley.com/ideas/p2p-marketplace-lending

[15] "The rise of peer-to-peer (P2P) lending", Nasdaq, retrieved April 26, 2019 from http://www.nasdaq.com/article/the-rise-of-peertopeer-p2p-lending-cm685513

[16] "Small Business, Big impact", Funding Circle, retrieved April 26, 2019 from https://static.fundingcircle.com/files/uk/information-packs/small-business-big-impact-cebr-report-315de033.pdf

Low administrative costs and no risk exposure unlike in case of a bank are associated with low interest margins. This cost advantage of P2P platforms leads to relatively low fees for the borrowers as Milne & Parboteeah (2016) argue.
Milne claims that after the global financial crisis at the beginning of the 21 century P2P loans made it possible to obtain funds for companies and individuals not meeting more stringent criteria set by banks. This is thanks to the fact that there have been alternative lenders willing to take on the risk (Milne & Parboteeah, 2016)). These facts imply widened access to funds which is supported by number of studies. (Jagtiani & Lemieux, 2018) (de Roure, Pelizzon, & Tasca, 2016).

P2P loans might also represent and interesting investing opportunity as based on their desired expected return investors can choose the loans they will invest in. Even though P2P investors, unlike financial institutions, do not have a large amount of funds for investing the possibility to partially fund many loans made effective diversification possible as Guo, Zhou, Luo, Liu, & Xiong (2016) note. Diversification enables to reduce the risk faced by lenders which will be shown in later chapters. Also, investors are typically encouraged by P2P platforms to diversify their portfolio. This is typically done be imposing restrictions on the maximum amount that can be invested in one loan. Investors can also benefit by using an auto-invest tool, offered by some platforms, which gives the investors the opportunity to automatically invest their money based on the set of criteria, mainly the target return. Such tool finds the right composition of the portfolio to produce the desired expected return. Among the P2P investors around 95 percent in the US and 75 percent in Europe use the auto-selection process. (Claessens et al., 2018)

As Milne and Parboteeah (2016) point out, investing in P2P loans offers better rates of return compared to the rates available on bank deposits partly due to the cost advantages of P2P platforms. In the Czech Republic the interest rates on the saving accounts have been declining during the last few years. Nevertheless, as of 2019, the interest rates on saving accounts started to grow slowly. Currently (Mai 2019), it is possible to find banks offering around 1 % interest rate on their saving account such as the Trinity bank[17].

[17] Trinity bank, retrieved April 25, 2019 https://www.trinitybank.cz/lide-sporici-ucty-vyhoda-plus/

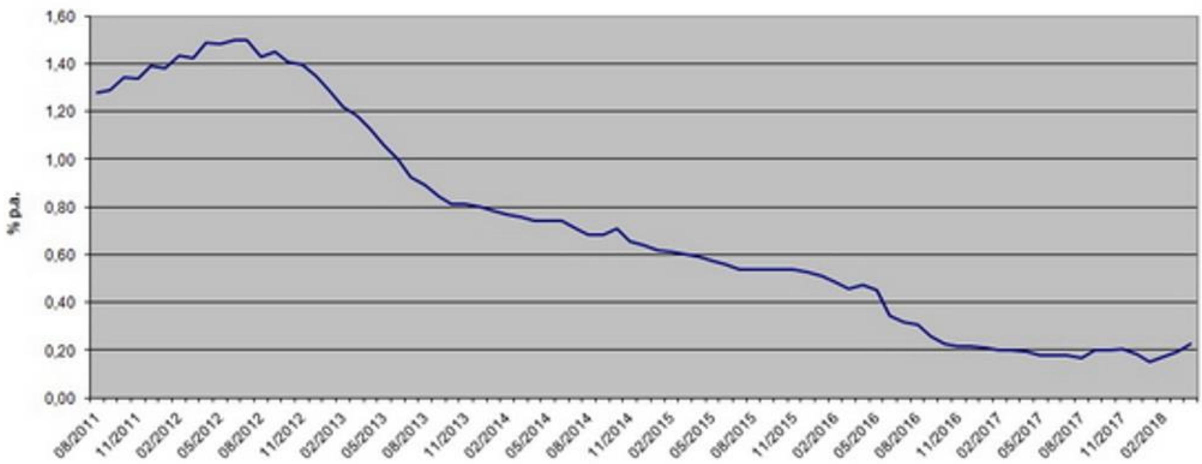

Figure 1.5: Average interest rate on savings accounts in the Czech Republic for 100 000 CZK[18]

Similarly, the yield of the Czech government bond offers relatively low rates of return (see figure…) compared to Zonky which promises average rate of return of 6%[19]. This makes Zonky attractive even for inexperienced investors as no special skills are required to start investing on Zonky. The higher expected return, however, does not come without a cost and there are number of risks as discussed later.

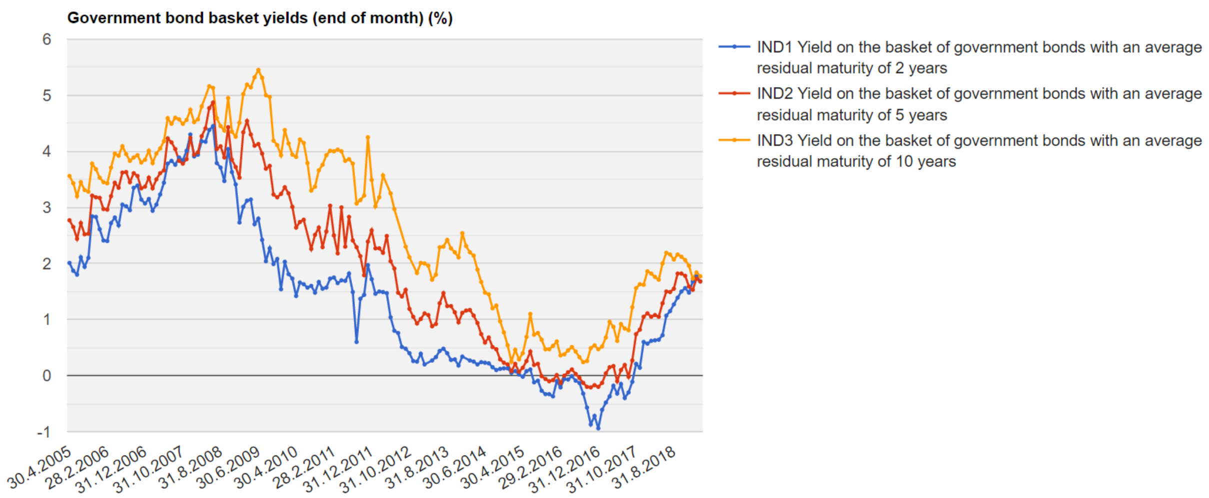

Figure 1.6: yield of the Czech government bond[20]

[18] Finparáda, retreived April 5, 2019 from https://finparada.cz/4961-Zebricky-sporicich-uctu-terminovanych-vkladu-a-Sporoindex-v-dubnu.aspx
[19] Zonky, retrieved April 5, 2019 from https://zonky.cz/otazky-a-odpovedi-investor
[20] CNB, retrieved April 29, 2019 from https://www.cnb.cz/cnb/STAT.ARADY_PKG.VYSTUP?p_period=1&p_sort=2&p_des=50&p_sestuid=22049&p_uka=1%2C2%2C3&p_strid=AEBA&p_od=200004&p_do=201904&p_lang=EN&p_format=4&p_decsep=.

Technology is also part of the advantage. Banks spend a great amount of money on technology, however the majority goes towards maintaining the existing systems, rather than on innovations. In 2012 a research showed that almost 80 percent of banks expenditures on technology went on maintenance. (Lodge, Zhang, & Jegher, 2015). On the other hand, P2P providers can design and implement systems that take advantage of new technologies, without being limited by the need for continuity with older systems which in turn allows them to offer better quality service to borrowers, by making the loan application and management fast, transparent and flexible as well as to the lenders by making it easy for them to invest and track the current status of their investments. Milne & Parboteeah (2016) confirm that the innovations which characterize P2P business provide greater transparency, flexibility and higher convenience for the customers.

1.4 The risks of P2P lending

Despite the advantages of P2P lending there is number of risks regarding frauds, identity theft, money laundering, consumer privacy, data-protection violations and terrorism financing (Chaffee & Rapp, 2012). The first point, the investor must be aware of, is the uncertainty of the investment returns. As already mentioned, the loans are not collateralized. What Lending Club states in its Investor Agreement can be generalized for all P2P platforms. The agreement says that Lending club does not guarantee that investor will receive any portion of the principal or interest which investor should receive according to the agreed terms. Also, no expected returns are guaranteed by the platform[21]. When a borrower defaults, investor must hope that P2P platforms have a good system for collecting defaulted debts. Furthermore, lenders of such sites have no possibility of independent pursuance of collection on these unpaid parts of their investment as (Chaffee & Rapp, 2012) argue. For instance, as noted in later chapters of this thesis, Zonky is not obliged to enforce the remaining overdue debt which makes it rather unlikely for an investor that Zonky will put significant effort into the enforcing process once it is no more interested in attracting investors. According to the Prosper's 2017 statistics, only 7 to 8 percent of the charge off principal was successfully collected as a result of recovery operations[22].

[21] "Investor Agreement", LendingClub, retrieved April 20, 2019 from https://www.lendingclub.com/legal/investor-agreement
[22] "Prosper performance update: January 2017", Prosper, retrieved April 25, 2019 from https://www.prosper.com/about-us/wp-content/uploads/Performance_Update_January2017.pdf

Also, the models used by the main P2P platforms were shown to be imperfect. The data supplied by the applicants were often unverified and inaccurate[23]. These facts imply worsen possibility for lenders to determine accurately the creditworthiness of borrowers as Chafee and Raf (2012) point out. Freedman and Jin (2008) states that the borrower can only observe categorical credit grade for each borrower but not the exact credit score.

Furthermore, individual lenders might lack the professional skills needed to predict and screen risks. According to the same authors, even if investors have the necessary skills they might lack the incentive to do the analysis before and after because they invest in many loans to diversify their portfolio. Another issue is the accuracy of the credit ratings regarding the performance of the loans due to limited amount of historical data.

Liquidity of such investment might also be a problem. Some of the loans are granted for several years. Even though there is a possibility of reselling the loan some platforms restrict these sales making this kind of investment illiquid. In case of Zonky it cannot be used in many cases due to the strict selling rules which do not allow to sell any loan with bad past performance as described in the chapter about the type of markets on Zonky platform. Besides that, there is uncertainty regarding the future of platforms and consequences of platforms' potential bankruptcy or frauds as happened in China recently[24]. As Qian & Hu (2019) notes, the number of problematic or closed platforms has been generally rising recently. Wei et al. (2015) considers fraud to be among the major risks P2P investors are facing. In addition to that there is uncertainty about future regulation which will affect the P2P business.

Kirby & Worner (2014) also mention that cyber risk is to be considered due to the fact that many P2P platforms are new and might not be able to deal with cyberattacks.

1.4.1 Information asymmetry

Another issue relating the P2P lending is the information asymmetry. Information asymmetry is a situation when one of the two parties involved in the business has access to relevant information which the other party does not have. Usually information asymmetry is associated with higher costs incurred. It increases the probability that the party having this information will try to behave opportunistically, in order to increases its potential benefit. The problem

[23]"The Gamble of Lending Peer to Peer", The New York Times, retrieved April 20, 2019 from https://www.nytimes.com/2011/02/05/your-money/05money.html
[24] "Chinese P2P lending bubble quietly bursts", The Epoch Times, retrieved April 18, 2019 from https://www.theepochtimes.com/chinese-p2plending-bubble-quietly-bursts_2208086.html

arises across different fields of finance industry. Adverse selection and moral hazard are examples of behavior connected to information asymmetry.

Moral hazard is quite usual in the insurance sector when the insured person increases their risk exposure after taking out insurance. Moral hazard in P2P lending might arise when the borrower uses the obtained funds for another purpose, possibly a riskier one, than what he initially stated when applying for a loan. For instance, instead of using the money for debt consolidation, as he claims, the debtor might use it to finance his start-up which involves much more risk and which therefore leads to higher probability that the loan will not be fully repaid.

The classic example is used to demonstrate the problem of adverse selection is the market for lemons a used by the economist Akerlof in 1970. Akerlof (1978) uses the model of second-hand market for cars to show that due to the information asymmetry only the low-quality cars are left behind (so called lemons) on this market. As Stiglitz & Weiss (1981) point out, Akerlof's market for lemons can be used for P2P loans as well. As an example, they consider two applicants with similar characteristics but at the same time one borrower having better credit history compared to the second one. Traditional providers could observe these differences and therefore treat both applicants differently. However, since a P2P platform assign them to the same risk category, say D, due to their similarity for P2P lenders they seem to be identical in terms of risk. According to Akerlof, this will lead to a situation when applicants with grade D- will be more attracted by the offered interest rate (corresponding to category D) than D+ applicants who are likely to have better payment morale.

Stiglitz & Weiss (1981) also claim that information asymmetry might lead to the so-called credit rationing which is a situation when lenders are unwilling to provide additional funds even for higher interest rates. (59)

1.4.2 Credit risk

P2P lending involves nearly all main major types of risk which are present in traditional financial intermediation, namely credit risk, interest rate risk, market risk, liquidity risk, foreign exchange risk and operational risk. (Moenninghoff & Wieandt, 2013) There is also the

risk of default of the intermediator. Among these the credit risk is the one which might affect investors the most.
Credit risk can be described as the risk associated with the possible failure of the borrower to repay the principal or interest payments in accordance with agreed terms. The goal of the lender should be to minimize this risk. The P2P providers group borrowers into several risk classes according to the level of credit risk, while the riskier borrowers have to pay higher interest rate. Usually this level is determined according to several different criteria such as the credit history, FICO score, income and other personal characteristics of applicants.
The problem is that peer-to-peer loans are usually unsecured meaning no collateral is available. In other words, there is no asset which serves as a security for the loan. Generally speaking, collateral can be seized by the lender in case of borrower's default. Due to missing deposit insurance and no promise of returns lenders must bear higher risk but are compensated by higher expected returns. (Milne & Parboteeah, 2016) However, exceptions can be found. For instance, Mintos, a P2P provider headquartered in Latvia, offers 2 kinds of loans: secured loans with collateral as well as unsecured without any collateral[25].

Some platforms try to mitigate the risk of loan default for the investors by maintaining a contingency fund which is supposed to top up investors' losses caused by a loan default. (Claessens et al., 2018). Besides that, some platforms set a minimum FICO score which an applicant is required to have. For example, for LendingClub this limit is equal to 640[26]. Second, the typical loan size is usually small. For Prosper the maximum amount which can be borrowed ranges between USD 2000 and USD 40 000[27]. For Zonky this between CZK 20 000 to CZK 750 000 which is even less. As Emekter, Tu, Jirasakuldech & Lu (2015) believe, such small amounts imply that P2P loans are microloans which pose a small potential loss. From the perspective of an investor, the portfolio's default risk can be mitigated by diversification as already mentioned.

Recent data show, that the performance of fintech loans has decreased recently. Higher default rates on main platforms in China, GB and US reduced returns of investors (see Figure

[25] Mintos, retrieved April 2, 2019 from https://www.mintos.com/en/faq/about-loans-faq/what-kinds-of-collateral-are-held-for-loans-faq/
[26] "Components that make up a FICO score", LendingClub, retrieved April 1, 2019 https://blog.lendingclub.com/components-that-make-up-a-fico-score/
[27] "How much can I borrow?", Prosper, retrieved April 2, 2019 from https://prosper.zendesk.com/hc/en-us/articles/208500656-How-much-can-I-borrow-

1.7). Recent loan-default rates also went up in Korea[28]. Furthermore, high share of platforms identifies the risk of higher default-rates as high or very high (see Figure 1.8). Such development was in stark contrast to the situation of banking sector which experienced time of very low rates of non-performing loans. This might imply that in order to expand some P2P platforms were willing to provide loans to riskier borrowers (Claessens et al., 2018).

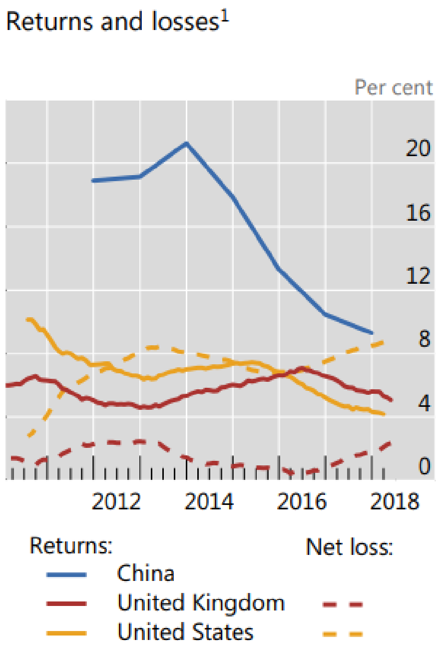

Figure 1.7: Returns and losses – main P2P lending markets (Claessens et al., 2018)

[28] "Financial stability report (June 2018)", Bank of Korea, retrieved April 5, 2019 from https://www.bok.or.kr/eng/bbs/E0000737/view.do?nttId=10046849&menuNo=400042&pageIndex=1

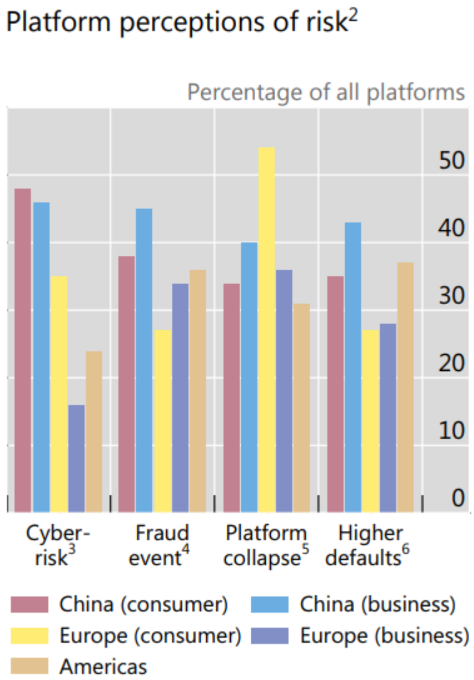

Figure 1.8: Perception of risk (Claessens et al., 2018)

1.5 Market mechanism

Generally, there are two kinds of matching process which is also being referred to as the market mechanism there are two different approaches used by P2P platforms. As Wei and Lin (2016) finds, the type of market mechanism can affect the behavior of lenders as well as of borrowers.

The first one is an online auction approach which typically relies on the supply and demand for loans. The borrowers indicate the maximum interest rate they are willing to pay on their loans and lenders indicate the minimum rate they require for given level of risk. New platform borrowers are than matched with lenders who want to provide loans. An automatic ‘reverse auction’ is then conducted. The interest rate payable on the loan is gradually increased until the number of bids is sufficient to fully fund the loan. The winner of the auction are investors offering the lowest interest rate. Therefore, if the interest rate is at the level which is not higher than the maximum rate the borrower is willing to pay the loan is funded. Otherwise it is rejected.

The second approach is based on automatic matching of borrowers and lenders at announced interest rates for each risk category. This can possibly lead to delays in the matching process because the number of lenders and borrowers typically is not the same. However, the interest rates can be adjusted over time to avoid this issue. (Milne & Parboteeah, 2016)

1.6 Regulation

In order to mitigate the risk exposure associated with disadvantages of P2P lending as discussed earlier, regulation is necessary. Some banks are directly involved in P2P lending which is another reason why P2P lending must be regulated as the banking sector is heavily regulated. For instance, Prosper and Lending club use model in which banks originates loans to individual borrowers and these loans are then sold to investors (Chaffee & Rapp, 2012). However, according to Chaeff there are two things hindering coherent regulation. Firstly, P2P lending is quite a new phenomenon whose impact might be unclear for regulators. Secondly, it might be rather hard to create a single regulatory regime owing to the fact that there are lots of P2P lending models and new models are being created (Chaffee & Rapp, 2012).

Generally speaking, the intensity of regulation is likely to affect the P2P lending market. (Claessens et al., 2018) The regulators should understand how the P2P lending affects the economic stability, i.e. whether economic cycles are amplified or reduced by peer-to-peer financial networks. For example, if consumers substitute secure deposits with risky loan investments, increasing loan default rates during an economic downturn might negatively affect their consumption behavior and further depress economic activity. Nevertheless, the effect of tighter regulation can be ambiguous. On one hand tighter regulations might lead to trust in P2P lending. On the other hand, it might make entrance and business activity in the market harder as Claessens et al. (2018) point out. Study suggests that there is a negative nonlinear relationship between the level of regulatory stringency (see Figure 1.9), as measured by the World bank's index called Bank regulation and supervision survey, and the level of P2P credits per capita (in this case P2P lending called fintech lending). (Claessens et al., 2018)

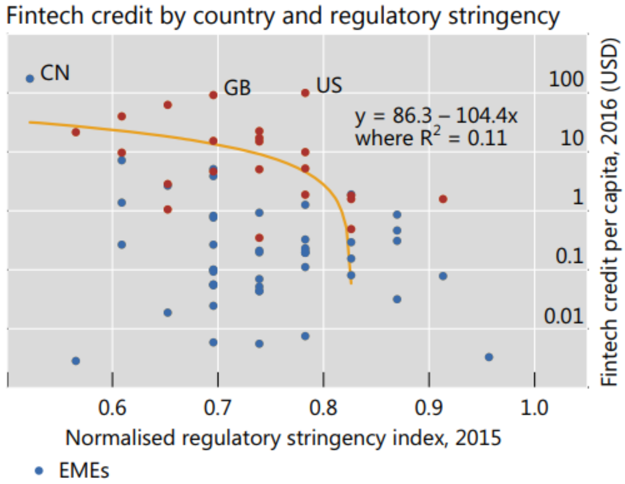

Figure 1.9: relationship between regulation and P2P credit [29] per capita (Claessens et al., 2018)

Studies also found that more stringent banking regulation deters fintech credit activity (Claessens et al., 2018). Author suggests that P2P regulation might be more liberal in countries where banking regulations are more liberal while it is harder to enter the P2P business in jurisdictions with strict banking regulations.

1.6.1 Regulation – UK, US, China

US

The US P2P industry was affected by the decision of the Securities and Exchange Commission. In 2008 SEC accused Prosper Marketplace of selling unregistered securities - the loans violating the Section 5 of the Securities Act of 1933. (Mariotto, 2016) Therefore, it was necessary for Prosper Marketplace to be registered with SEC for law compliance. Lending Club registered loans as securities one month earlier with the SEC which gave him advantage over other platforms and consequently it was able to win big share of the American market. Consequently, P2P loans have to be registered with the SEC as it not permitted to sell securities without approval (Slattery, 2016).
Every state in the US uses different approach to regulation. Some states banned the P2P lending, other allowed it using the SEC rules (Huang, 2018).

[29] Note: fintech credit used as a synonym for P2P loan

UK

In the UK the P2P lending market has been regulated by the Financial Conduct Authority since April 2014 by publishing the Policy Statement 14/4 called "The FCA's regulatory approach to crowdfunding over the internet, and the promotion of non-readily realisable securities by other media Feedback to CP13/13 and final rules". This document specifies rules for P2P lending as well as for investment-based crowdfunding. Each company intending to operate in P2P business has to be authorized by FCA[30]. Such company also has to meet certain requirements set by FCA. For instance, it has to introduce the business plan, prove to have adequate financial and non-financial resources as well as to have a website which demonstrates how the firm will operate if it is given the permission[31]. Besides FCA, in the UK there is a self-regulatory Peer-to-peer finance association (P2PFA). Even though the market is regulated, P2P investments are not protected by the Financial Services Compensation Scheme which is a statutory deposit insurance in the UK[32].

China

In China many platforms were negatively affected by the tight regulations in 2018 caused by several frauds and series of demonstrations of the investors. Before that the market was only lightly controlled by the government, characterized by high risk and high returns. However, after some scandals occurred, government stepped in. For instance, in 2015, Fanya Metal Exchange raised illegally more than RMB 40 billion as Huang (2018) notes. Few months later, it was discovered that another P2P platform called Ezu Bao was involved in a big fraud stealing RMB 50 billion from its investors. It is anticipated that this stricter regulation will cause number of Chinese P2P platforms to shrink from more than 1500 to only 50[33]. Another estimate is slightly more optimistic estimating that 300 companies will remain in the business[34]. As Huang (2018) points out, these changes might result in more collaboration between online lending platforms and traditional banks.

[30] FCA, page 6, retrieved April 14, 2019 from https://www.fca.org.uk/publication/policy/ps14-04.pdf
[31] FCA, paragraph 44, retrieved April 14, 2019 from https://www.fca.org.uk/publication/thematic-reviews/crowdfunding-review.pdf
[32] "How is your money FSCS protected?", FSCS, retrieved April 15, 2019 from https://protected.fscs.org.uk/banking/how-is-your-money-fscs-protected/
[33] "China's P2P lenders say regulation will cause industry collapse", Financial Times, retrieved April 15, 2019 from https://www.ft.com/content/eac2c2de-d050-11e8-a9f2-7574db66bcd5
[34] "China P2P Lending Crackdown May See 70% of Firms Close", Bloomberg, retrieved April 16, 2019 from https://www.bloomberg.com/news/articles/2019-01-02/china-s-online-lending-crackdown-may-see-70-of-businesses-close

1.6.2 Regulation – Czech Republic

The P2P business in the Czech Republic is regulated by the CNB. It is based on two acts in the Czech legislation. Namely the Payment System Act and Consumer Credit Act. In the Czech Republic it is necessary for each platform to have obtained the payment institution license. Such platform should take care of the matching process, assess creditworthiness of the applicants as well as to ensure that the whole loan process and receipt of repayments works as it should.

In 2016 an amendment of the Consumer Credit Act was enacted whose goals were primarily consumer protection, harmonization of European legislation and creation of uniform conditions for all market participants. Consequently, non-banking credit providers have to be licensed[35]. In January 2019 there were 87 non-banking credit providers - Zonky being one of them. In order for a non-banking institution to be licensed, some requirements must be met. For example, the company applying for it must have at least 20 million initial capital and its management must seem trustworthy to CNB[36]. Also, number of rules must be kept when a company is operating. For instance, any kind of money laundering has to be avoided, the administrative processes should be in accordance with the CNB rules as well as the process of assessing the creditworthiness must be adjusted[37].

2. ZONKY

Zonky is a Czech P2P lending platform providing credit loans. It was founded in 2015 thanks to the fond Home Credit Lab N.V which is a mother company of Home credit - a Czech non-banking institution providing credit loans. It is part of Home Credit Group belonging to the international investment group PPF[38]. Its activities are supervised by the Czech National Bank. It works online as well as using several local branches[39] and the platform can be accessed from PC as well as from mobile device using Android or IOS as operational system.

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[35] "Tomáš Nidetzký: Nebankovní poskytovatelé úvěrů musí mít nově licenci", CNB, retrieved April 15, 2019 from https://www.cnb.cz/cs/o_cnb/vlog-cnb/Tomas-Nidetzky-Nebankovni-poskytovatele-uveru-musi-mit-nove-licenci/

[36] "Kdo smí půjčovat peníze? Přísná pravidla ČNB přežil jen zlomek poskytovatelů úvěrů", Aktuálně.cz, retrieved April 15, 2019 from https://zpravy.aktualne.cz/ekonomika/seznam-oficialnich-nebankovnich-poskytovatelu-uveru-klesl-na/r~e64f72f6fd3c11e8af000cc47ab5f122/?redirected=1557424095

[37] "Dohledový benchmark č. 3/2016", CNB, retrieved April 17, 2019 from https://www.cnb.cz/export/sites/cnb/cs/dohled-financni-trh/.galleries/vykon_dohledu/dohledove_benchmarky/download/dohledovy_benchmark_2016_03.pdf

[38] Peníze.cz, retrieved April 18, 2019 from https://rejstrik.penize.cz/03570967-zonky-s-r-o

[39] Zonky, retrieved April 18, 2019 from https://zonkysetkani.cz/

The advantage for the borrower is that he might get a loan easily without any collateral. For the lender Zonky might represent an interesting investment opportunity.

2.1 Participants

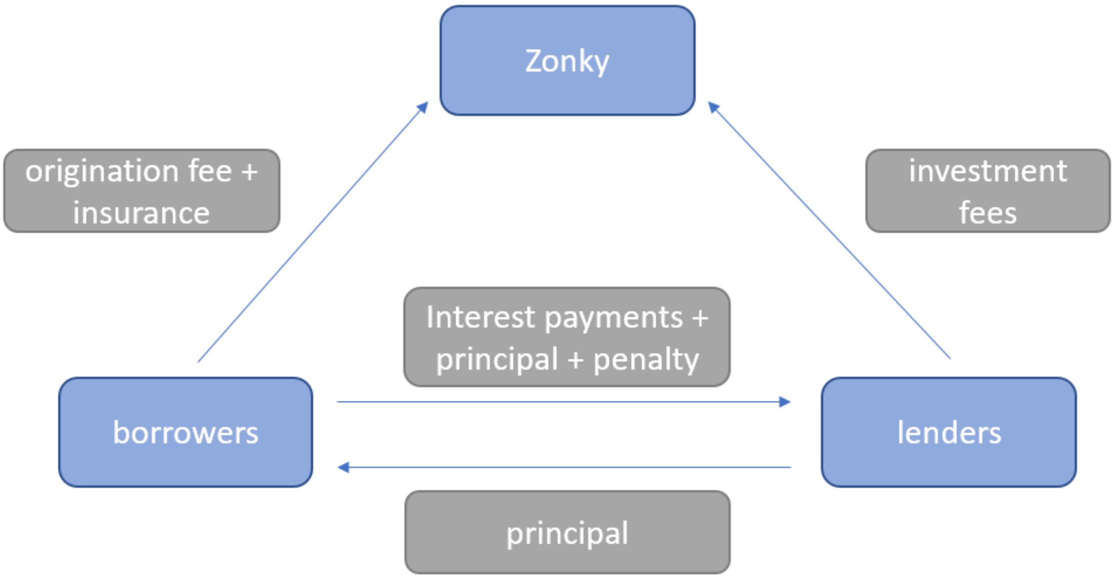

Figure 2.1: cash flows between participants on Zonky

There are three kind participants: Zonky, which has the role of intermediator, investors and borrowers. Figure 2.1 shows a simplified representation of the cash flows between those three participants.

The role of Zonky is to match lenders with borrowers and to make sure that both parties behave according to the agreed terms. In the case of default, Zonky is entitled to enforce the remaining debt. However, it is not obliged to do so[40].

The installments are received by Zonky which keeps small part of it to cover the origination fees and insurance. The rest amount of the money is passed on the investors. The interest payments represent the profit for them.

An individual can become an investor under the assumption that he is at least 18 years old. His identity must be verified using at least two personal documents such as ID card, passport or driving license. The registration can be easily completed within several minutes online.

[40] "Zonky Obchodní podmínky participace na spotřebitelských úvěrech" https://zonky.cz/dokumenty#obecne accessed 20.4.2019

The process of providing loans is regulated by related acts primarily by the Consumer credit act. Any individual wishing to obtain a loan must also be at least 18 years old. As in the case of investor his identity must be verified using copy of two personal documents. Also for every applicant it is necessary to go through the whole loan application procedure. The purpose of this whether the applicant meets criteria for a loan and if so it should that the applicant will get loan under the most suitable conditions. Firstly, the confirmation of his level of income in the form of salary of account statement must be provided. Other sources of information about the applicant are public registers such as the Commercial Register, Trade Licensing Register, Land register or Insolvency Register as well as the public data from social media. Furthermore, information from the following three registers are evaluated[41].

Non-banking client information register is the first one. It is operated by the Czech Non-Banking Credit Bureau. This is a voluntary association of legal entities founded in 2004. Its purpose is to facilitate the information sharing among loan and leasing companies mainly data regarding the creditworthiness, solvency and payment discipline of their clients who can be individuals or legal entities. CINBR is the place where this information is stored[42]. The second register called Client Information Bank Register is operated since 2000 by the Czech Banking Credit Bureau. It is a database with information similar to that of CINBR regarding client's solvency and creditworthiness. However, this information comes and is shared among the members of CIBR - Czech banks[43]. The last of these three registers is SOLUS - interest association of legal persons. SOLUS aims for prevention of overindebtedness of clients of its members, reduction of potential financial losses to the creditors and increase the enforceability of the existing overdue debts. Its members are companies from different economic areas such as non-banking financial institutions, banks, telecommunication operators, energy distributors and other companies[44]. Zonky is the only Czech P2P platform which can access CINBR and CIBR[45].

Apart from registers, Zonky can also get more information about applicant's payment morale from the O2 telecommunication operator, if permission is given. Based on these data Zonky decides whether the applicant is eligible for a loan. If this is the case the final interest rate is

[41] " Zonky - pravidla portálu", Zonky, retrieved April 4, 2019 from https://zonky.cz/dokumenty#obecne
[42] Czech credit bureau, retrieved April 10, 2019 from https://www.crif.cz/home-eng/bureaus/non-banking-client-information-register-cinbr/
[43] Czech banking credit bureau, retrieved April 6, 2019 from https://www.cbcb.cz/caste-otazky/
[44] SOLUS, retrieved April 5, 2019 from https://www.solus.cz/en/about-association/
[45] "Informační memorandum nebankovního registru klientských informací", Zonky, retriever April 6, 2019 from https://zonky.cz/dokumenty

calculated for the applicant and he is given an offer. After signing the contract, the loan becomes available for lenders to be invested in.
The principal amount is provided by Zonky to the borrower if there are enough investors willing to provide funds. Occasionally the principal can be provided before the loan has been offered to lenders as an investment.

2.2 Investing

Investor can choose to invest in different type of loans according to his preferences as mentioned earlier. According to Zonky, the average rate of return is around 6 %. If profit is made it is subject to a tax rate of 15 %. There is no restriction regarding the quantity of loans the investor is allowed to invest in however it is possible to fund only a part of a loan which implies that every loan is funded by several lenders. The minimum amount which can be invested in one loan is 200 CZK. Moreover, there is a limit for the maximum possible amount which can be invested in one loan. This is the way how the platform encourages diversification. This limit depends on the number of loans the investor has already invested in. If no more than 100 investments have been made this limit is 5000 CZK per loan. For more experienced investors who have made between 101 and 200 investments it is equal to 10 000 CZK. The highest limit is 20 000 CZK for one loan and it applies for investors who have invested in more than 200 loans[46].

Zonky uses several criteria in order to determine the level of risk associated with the person asking for loan. Every borrower is put in one of the risk categories, which means that an investor can choose in which of these categories he wants to invest. Currently there are 11 risk categories. The least risky category, represented by the interest rate of 2,99% should be the least risky one while the interest rate for the riskiest category is 19,99% pa. Loans with the interest rate between 2,99% and 10,99 % are labeled as the least risky or low risk, 13,49% corresponds to medium level risk and 15,49% and 19,99% are described as risky[47]. However, investors must be aware of the fact that loans on Zonky platform are uncollateralized and therefore investors bear all the risk.

[46] "Parametry částek pro investování ", Zonky, retriever April 20, 2019 from https://zonky.cz/dokumenty#investori
[47] "Ratingy, které na Zonkym rozlišujeme", Zonky, retrieved April 18, 2019 from https://zonky.cz/otazky-a-odpovedi-investor

Another thing which a lender must consider are fees for the services which Zonky provides. These differ across the risk categories and they are higher for riskier categories as showed in Table 2.1.

Table 2.1: Interest rate at Zonky and the investment fees[48]

Interest rate	*Fee (p.a.)*
2,99%	0,2%
3,99 %	0,2%
4,99%	0,5%
5,99%	1%
6,99%	1,5%
8,49%	2,2%
9,49%	2,5%
10,99%	3%
13,49%	3,5%
15,49%	4%
19,99%	5%

Until September 2017 the fee was 1 % for every risk category. However, changed its fee policy which should enable it further expansion[49].
The fees are calculated on daily basis from the total amount currently invested which is the remaining unpaid principal the investor has invested. It is paid once a month always on the first day of respective month[50]. Investors do not pay fees anymore if the payment is more than 36 days past due[26].

2.3 Debt repayment

The debt must be repaid by borrower in regular monthly installments. The borrower is also obliged to pay fee accounting for 2 % of the principal amount[51] which is repaid with first several installments - usually within the first two or three installments. An early loan

[48] "Kolik stojí služba investory? ", Zonky, retrieved April 18, 2019 from https://zonky.cz/otazky-a-odpovedi-investor
[49] "Zonky nově upraví poplatky pro investory", https://www.zonky.cz/zonkytimes/zonky-nove-upravi-poplatky-pro-investory/
[50] „Zonky sazebník investora", https://zonky.cz/dokumenty, accessed on 18.5.2019
[51] "Na čem vydělává Zonky? ", https://zonky.cz/otazky-a-odpovedi-investor

repayment can be done without being penalized for that[52]. The interest rate is calculated on the ACT/365 basis. The final installment amount constitutes of principal, interest repayments, insurance (if desired) and fee.

2.4 Types of market

There are two types of market on Zonky. The primary market is the place where recently granted loans are offered for investing for the first time. Investors can set several parameters to find the right investment opportunities such as maturity of the loan, desired interest rate, insolvency insurance of the borrower as well as the purpose of the loan and the source of income of the borrower. The loans satisfying the settings are displayed. Decision of the investors might also be affected by the story, which is connected to the listed loans, written directly by the borrower which provides the investor with brief information about the aim of financing as well as his financial situation. Nevertheless, many borrowers choose not to write any story. This decision is up to them. So far only 23,55% of the borrowers decided to write a story[53]. Another possibility how to get more familiar with the situation of a loan applicant is to directly ask him a question related to the loan application.

The second kind of market on the Zonky platform is the secondary market. It allows an investor to sell them their investments to another investor. This is also the only way how the loan can be liquidated before its maturity. However, if an investment is resold earlier than 12 months after investor invested in it, there is a fee which accounts for 1,5 % from the selling price of the investment. Otherwise there are no fees associated with selling a part of a loan[54]. Nevertheless, an investment that is currently overdue or which has ever been more than 1 day past due cannot be resold at the secondary market.

[52] "Co je Zonky?", https://zonky.cz/otazky-a-odpovedi-investor, accessed on 15.4.2019
[53] Author's own calculation based on provided data
[54] "Sazebník investora", Zonky, retrieved April 18, 2019 from https://zonky.cz/dokumenty

2.5 Default

If the borrower cannot honor his obligations, there are penalties. Namely, there can be 500 CZK penalty for every delayed payment. In special cases such as when two or more payments are delayed or if one installment is more than three months overdue or due to some other violations of the agreed terms the investor is requested to repay the remaining debt immediately and the loan is regarded as defaulted. This situation can bring additional fees[55] for borrowers. Any penalty collected is then received by investors. In some cases, it might be necessary for Zonky to pursue the recovery of the remaining debt by legal means. In such case there is a 30 % fee calculated from the amount which has been eventually collected[56]. If an outstanding loan is more than 5 years due the platform has no more obligations to transfer any later obtained part of the debt to the investors.

The borrower can protect himself against insolvency by taking out insurance provided by the platform. This enables the debtor to put off the instalment payments until up to 12 months in case of losing source of income or being unable to work because of illness. This costs the borrower extra 6,9 % of the monthly installment[57].

2.6 Zonky vs competitors

The level of P2P lending activity in the Czech Republic is low compared to countries like UK, USA or China. Zonky is currently the leading P2P company in Czech Republic. Nowadays there are several competitors in the Czech Republic, most of them using a different business model. We will introduce three of them.

The first platform is Bankerat which has been operating since 2010. So far it has helped to lend almost 1 billion CZK. Currently there more than 54 000 registered users. There are no fixed interest rates as on Zonky platform but the interest rate can range anywhere between 9 % and 55 % p.a. The process of matching uses the auction system[58]. The loan applicants specify the maximum interest rate they are willing to pay and they receive offers from investors which they can decline or accept. Also, no limit regarding the maximum amount which can be invested by an investor is set, unlike in case of Zonky which set limits for maximum amount invested in

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[55] "Zesplatnění ", Zonky, retrieved April 21, 2019 from https://zonky.cz/otazky-a-odpovedi
[56] "Sazebník investora ", Zonky, retrieved April 21, 2019 from https://zonky.cz/dokumenty#obecne
[57] "Rámcová pojistná smlouva", Zonky, retrieved April 21, 2019 from https://zonky.cz/dokumenty
[58] Bankerat, retrieved April 25, 2019 from https://www.bankerat.cz/pujcka/

one loan. This gives the potential investor the choice to lend the whole amount requested by the borrower. The investor's fee accounts for 1 % of the remaining unpaid principal and interest payments[59]. On the other hand, the borrower must pay 5 % of the principal amount as a fee[60]. The process of lending might not be anonymous as in case of Zonky because of the fact that the investor can request copy of personal documents from the borrower.

The second competitor is a platform called Prestito[61] operating since 2012 on the Czech market. Individuals can make loan applications by placing an online advertisement on the platform website specifying the requested principal amount and interest rate. The loan principal can range from 10 000 CZK to 1 000 000 CZK while the term is unlimited. The minimum amount of investment is 5000 CZK which makes diversification hard. What is unique compared to the other two competitors is the possibility to earn commission by inviting individuals to borrow money on the platform. Commission of 3 percent is earned from the principal amount borrowed by the invited individual. As in the case of Zonky no extra fee is charged for early repayment.

Another platform using the auction matching system is called Banking online[62]. It gives also investors the chance to start auction. Up to 500 000 CZK can be borrowed for a period lasting between 6 and 60 months. Also, the interest rate is limited and it can range anywhere from 3% to 15 %. The borrowers pay 1,5 % fee from the borrowed amount. On the other hand, the investors pay 0,8% from every payment received by the debtor.

3. LITERATURE REVIEW

Even though P2P lending is quite a new phenomenon there have been many studies dealing with this topic. Hulme & Wright (2006) claim that the emergence of P2P lending stems from the social trends and demand for new types of relationships in financial sector in the new information age. Even though banks and P2P platforms have different business model, Everett (2015) sees strong similarities between the traditional lending and P2P lending. Furthermore,

[59] "Poplatek věřitele ", Bankerat, retrieved April 10, 2019 from https://www.bankerat.cz/investice/poplatek-veritele/
[60] "Poplatek dlužníka", Bankerat retrieved April 10, 2019 from https://www.bankerat.cz/pujcka/poplatek-dluznika/
[61] Prestito, retrieved April 20, 2019 from http://www.prestito.cz/clanek/13/tiskova-zprava-ke-spusteni-aukcniho-portalu-prestito-cz
[62] Banking Online, retrieved April 20, 2019 from https://www.banking-online.cz/

he argues that the idea of P2P lending does not represent a completely new business model. Käfer (2018) shares the view but believes that P2P is riskier than the traditional banking. De Roure et al. (2016) finds that P2P loans are especially attractive for applicants who were rejected by traditional financial intermediaries. These applicants are willing to accept higher interest rate offered by P2P platforms. Maudos & Fernández de Guevara (2004) argue that operating cost is the most important factor for explanation of interest margins in case of banks. These operating costs are than passed on their clients unlike in P2P lending.

Number of studies focus on the risk associated with P2P lending. The risk which particularly affects P2P lending is the information asymmetry. According to Diamond & Dybvig, (1986) the information asymmetry in traditional lending is mitigated by permanent monitoring of borrowers which does not happen in case of P2P lending. The cost of this monitoring is included in the interest rates Diamond (1984) which are generally higher for traditional providers. Lin (2009) recommends giving the lenders the possibility to monitor the borrowers to reduce the information asymmetry in P2P lending.

Some studies were denoted to the likelihood of the funding success. Herzenstein, Andrews, Dholakia, & Lyandres (2008) find out that demographic attributes such as race and gender do affect this likelihood although their impact is small compared to the effects of the financial strength of the borrowers. His results showed that individuals lend more fairly compared to the US financial institutions using discriminatory practices. According to Herzenstein et al. (2008) the determinant having the biggest impact on the funding success is the effort put by the borrower in providing personal information. Herzenstein, Dholakia, & Andrews (2011) demonstrate that there is a higher probability that lenders will bid on an auction with more bids but solely to the point when it has received the full funding which is referred to as herding behavior. Lin, Prabhala, & Viswanathan (2012) find that investors are willing to provide the requested funds faster if the borrowers are members of relational friendship networks. Wei & Lin (2016) deal with the matching mechanisms and the probability of a loan being funded. According to them, the matching mechanism where the interest rates are set by the platform offers higher probability of loans being funded. The results of Freedman & Jin (2014) show that for borrowers with social ties the probability of getting loan funded and receiving higher interest rate is higher.

As mentioned in the previous chapters, the credit risk is among the major risks. Consequently, several studies deal with the determinants of default. These studies uses different approaches among which are logistic regression, Markov chains, linear discriminate analysis and other. Iyer, Khwaja, Luttmer, & Shue (2009) find out that credit score, number of current delinquencies, total delinquencies, debt-to-income ratio and loan amount have significant impact on loan defaults. According to study of Everett (2015), the credit score, age of the borrower, home ownership and loan amount are the significant variables which helps to predict a default of P2P loans. On the other hand, the results of Guo, Zhou, Luo, Liu and Xiong (2016) shows that FICO score, loan amount, homeownership and debt-to-income ratio are significant. The results of the research conducted by Wei & Lin (2016) indicates that loans are more likely to default under the market mechanism of posted prices. This leads to a lower total welfare as investors' ROI and surplus are lower. Emekter, Tu, Jirasakuldech & Lu (2015) uses data from Lending Club to demonstrate that higher interest rate charged on the riskier borrowers is not high enough to compensate the lenders for the higher likelihood of loan default and they recommended attracting borrowers with high FICO score and high income in order for Lending Club to sustain their businesses.

Čermáková (2018) shows that among the personal characteristics of debtors on Zonky, which have the highest effect on the probability of the loan being repaid are education, age, income, number of children, martial and employment status.

With regard to the loan purpose, Serrano-Cinca, Gutiérrez-Nieto, & López-Palacios (2015) discover that loans for small businesses are the riskiest types of loans while the loans for wedding are the least risky types.

Some studies deal with the evaluation of portfolio performance. Klafft (2008) argues that lenders can profit from investing in P2P loans if they follow a sound investment strategy. Singh, Gopal, & Li (2008) focus on risk and return of investments using the data from Prosper. They calculate the ROI for each loan and find the optimal portfolio by finding the efficient frontier. Also, they assume zero correlation between loans. They discover that loans with lower credit grade are more efficient in terms of risk and return compared to those with higher credit grade. Guo et al. (2016) use the so-called instance-based approach, trying to identify loans with similar attributes to predict the performance of new loans. The logistic regression model and the kernel regression is used for finding the optimal portfolio. Furthermore, Guo et al. (2016) argue that P2P lending can be seen as a typical portfolio selection problem based on the MPT. Besides that, they assume that the correlation between loans is zero. This contradicts the findings of Polák (2017) who finds that covariance is significantly different from zero. He uses the logistic regression and mean-variance approach to find the optimal portfolio but obtains different results based on the assumption he makes about the correlation between loan categories which implies that the correlation between loan categories cannot be ignored. As Chi, Ding and Peng (2019) note, the mean-variance optimization approach faces the problem of deficiency of the historical observations (79) Chi, Ding and Peng (2019) proposes a data-driven robust portfolio optimization model which is based on relative entropy constraints. Bock & Tichý (2017) do a short analysis to find the optimal portfolio on Zonky using Markowitz theory. However, they only use the information available on the website of Zonky without considering any correlation between loans and without any deeper analysis.

4. THEORETICAL CONCEPTS

We will start by defining the statistical measures and financial terms necessary for the empirical part.

4.1 Portfolio

The term portfolio refers to a combination of assets, such as stocks, bonds, commodities and so on. It can be built solely from one asset as well as from many different unrelated assets with different characteristics. Hence, the composition of a portfolio should reflect investor's preferences regarding the individual assets or the performance of the portfolio. Portfolio weight can be described as the percentage composition of a particular asset in a portfolio. Usually, it is the share of the value of a particular asset on the value of the whole portfolio[63]. Therefore, for every portfolio consisting of N assets it must hold that the sum of all weights must be equal to one (Equation 4.1).

$$\sum_{i=1}^{N} w_i = 1 \, , i = 1 \dots . N \tag{4.1}$$

[63] "Portfolio weight", Investopedia, retrieved April 15, 2019 from https://www.investopedia.com/terms/p/portfolio-weight.asp

It is also possible for an asset to have a negative weight which is called a short position, meaning that the investor sells an asset which does not belong to him (possibly by borrowing it, while being obliged to return it later).

4.2 Expected return

Due to the uncertainty regarding the future our best estimate of the portfolio's return, the expected return of a portfolio, can be computed as the weighted average of the expected returns of the assets which build the portfolio (Equation 4.2)

$$E(P) = \sum_{i=1}^{N} w_i * E(r_i), i = 1 \dots . N \qquad (4.2)$$

Where $E(r_i)$, the expected return of an asset, can be derived by the following formula (Equation 4.3).

$$E(ri) = \sum_{i=1}^{M} p_t * ri_t \qquad (4.3)$$

where:

$M\ is\ number\ of\ possible\ outcomes$

$p_t\ is\ probability\ of\ outcome\ t$

$ri_t\ is\ the\ rate\ of\ return\ for\ the\ asset\ if\ outcome\ t\ occurs$

The portfolio's expected return can also be written using the matrix notation as:

$$E(P) = w^T * \mu \qquad (4.4)$$

where:

$w^T\ is\ the\ 1\ \times k\ matrix\ created\ by\ transposing\ the\ matrix\ of\ weights$

$\mu\ is\ the\ k \times 1\ matrix\ of\ expected\ returns$

In our case the weights represent the share of individual loan categories in our portfolio and the expected returns are those of these risk categories.

4.3 Variance

Even though two portfolios have the same expected return they might differ in terms of the risk associated with investing in each of them. This risk associated with an asset is described by its standard deviation, which measures the investment's volatility in terms or returns. It is measured as the square root of the variance. Generally, the population variance of a finite population of size N is given by the Equation 4.5:

$$Var(P) = \frac{\sum_{i=1}^{N}(X_i - \bar{X})}{N}, i = 1 \ldots . N \tag{4.5}$$

where N is equal to the population size, $\bar{X}$ denotes the population mean and X_i is the value of one of the individual assets which the population consists of. Variance of a risk-free asset is zero. Variance of a portfolio consisting of two risky assets X and Y is given by Equation 4.6.

$$\begin{aligned} Var(aX + bY) &= a^2 * Var(X) + b^2 * Var(Y) + 2 * a * b * Cov(X, Y) = \\ &= a^2 * Var(X) + b^2 * Var(Y) + 2 * a * b * \sigma_x * \sigma_y * Corr(X, Y) \end{aligned} \tag{4.6}$$

where

$a, b = weights\ corresponding\ to\ the\ risky\ assets$

$\sigma_x = the\ standard\ deviation\ of\ X$

$\sigma_y = the\ standard\ deviation\ of\ Y$

$Corr(X, Y) = correlation\ between\ the\ RVs$

Generally, for a portfolio consisting of N assets with weight x the total variance of this portfolio is given by Equation 4.7.

$$\sigma^2 = \sum_{i=1}^{N}\sum_{j=1}^{N} \sigma_{i,j} * x_i * x_j \tag{4.7}$$

where
$x_i = weight\ of\ the\ i - th\ asset$
$\sigma_{i,j} = covariance\ between\ i - th\ and\ j - th\ asset$

For a graphical illustration see Table 4.1. It shows that portfolio variance is equal to the sum of all cells of a $N \times N$ matrix consisting of covariances of corresponding assets multiplied by their respective weights. If we do not consider weights (we would set them all equal to 1), we obtain a matrix which is generally called a variance-covariance matrix.

Table 4.1: Graphical illustration of portfolio's variance

	Asset 1	*Asset 2*	...	*Asset N*
Asset 1	$w_1^2 * Cov(1,1)$	$w_1 * w_2 * Cov(1,2)$	...	$w_1 * w_N * Cov(1,N)$
Asset 2	$w_2 * w_1 * Cov(2,1)$	$w_2^2 * Cov(2,2)$	...	$w_2 * w_N * Cov(2,N)$
$\vdots$	$\vdots$	$\vdots$		$\vdots$
Asset N	$w_N * w_1 * Cov(N,1)$	$w_N * w_2 * Cov(N,2)$	...	$w_N * w_N * Cov(N,N)$

Source: Author's own table

4.4 Covariance and correlation

To measure the relationships between returns on two risky assets we use a measure called covariance. It is positive when the returns have the same direction of movement and vice versa. Let X and Y be two random variables. The covariance between those two random variables can be calculated using the Equation 4.8.

$$Cov(X,Y) = \frac{\sum_{i=1}^{N}(X_i - E[X]) * (Y_i - E[Y])}{N} \tag{4.8}$$

This measure is used as an input for the variance-covariance matrix. An important fact is that covariance of a random variable with itself is equal to the variance of that random variable (see Equation 4.9)

$$Cov(X, X) = Var(X) \tag{4.9}$$

Covariance can be used to obtain correlation between the same random variables which is also a measure of dependence of these random variables (see Equation 5.0).

$$Corr(X, Y) = \frac{Cov(X, Y)}{\sigma_x * \sigma_y} \in < -1,1 > \tag{4.1.1}$$

4.5 Utility

The general assumption is that an investor would like to maximize his satisfaction he will get from investing in a portfolio. In economics this satisfaction is called utility level and it can be described by a utility function. A simple example of this function is given by Equation 4.2.1.

$$U = E(P) - 0{,}5 * A * Var(P) \tag{4.2.1}$$

where $E(P)$ denotes the expected return of a portfolio and $Var(P)$ is its variance. In the case of a portfolio consisting of risk-free asset the utility is equal to the rate of return of the RFA. The letter A represents the level of risk aversion of a particular investor. Hence, the utility function will be different for every investor based on his willingness to exchange risk for expected return. The higher the A the more risk averse the investor is. In case of risk friendly investor, the A would be negative, meaning higher risk results in higher satisfaction of the investor. A risk averse investor always prefers lower risk and higher expected return. The combination of all points which bring the same level of satisfaction for a risk-averse investor, the so-called indifference curve, is depicted graphically in Figure 4.1.

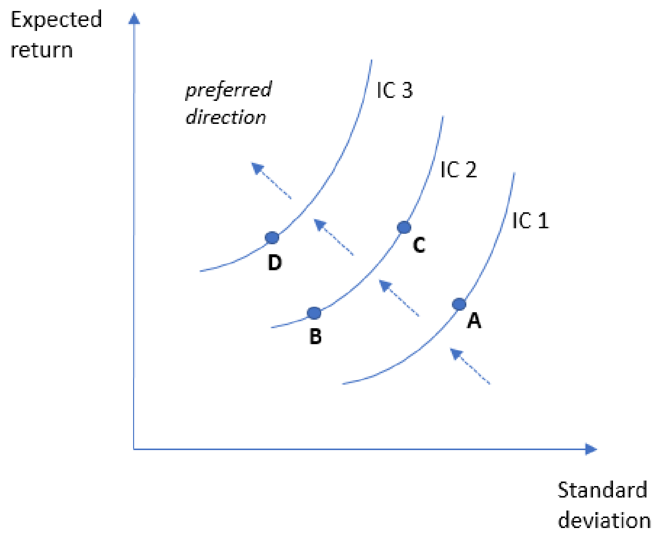

Figure 4.1: indifference curves[64]

The investor is indifferent between points lying on the same indifference curve (in this case points B and C). Points B and C are preferred to the point A. However, the point D is preferred to B, C as it lies on the utility curve with higher level of satisfaction.

4.6 Diversification

There are two sources of risk to a portfolio. The market risk, also called the systematic risk is the first one. It is the risk which affects all assets building our portfolio such as risk arising from the changes in inflation, interest rates or exchange rates. The second type of risk is the specific risk, also called unique. This kind of risk is asset-specific. In other words, it affects only the asset we are considering. This risk can be diversified away as the number of assets building our portfolio increases unlike the market risk. Therefore, as n, denoting the number of different assets in our portfolio, increases the overall risk of our portfolio approaches the level of market risk which cannot be diversified away.

[64] Author's own plot

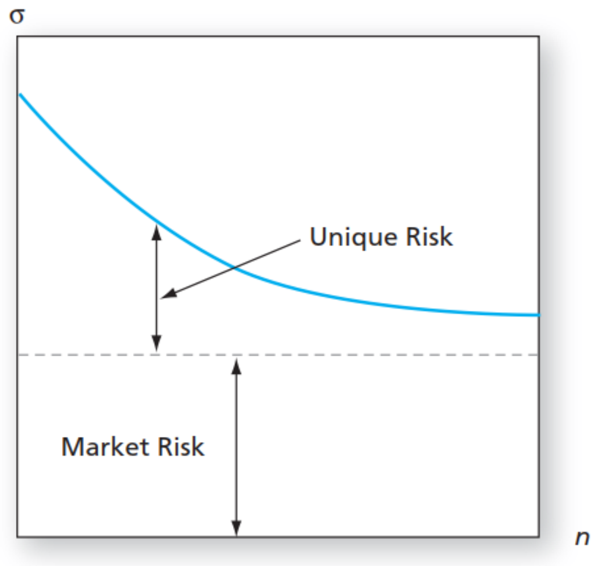

Figure 4.2: two sources of risk (Bodie, Kane, & Marcus, 2013)

Therefore, it is possible to lower the overall portfolio risk by diversifying it. The benefits of diversification can be first shown for a portfolio consisting of two assets. We have shown that the variance and the standard deviation which are both measures of the risk of a portfolio consisting of two assets are given by the following two formulas (Equation 4.3.1 and 4.4.1).

$$Var(w_1 * X + w_2 * Y) = \tag{4.3.1}$$
$$= w_1^2 * Var(X) + w_2^2 * Var(Y) + 2 * w_1 * w_2 * \sigma_x * \sigma_y * Corr(X, Y)$$

$$\sigma_p = \sqrt{w_1^2.Var(X) + w_2^2.Var(Y) + 2.w_1.w_2.\sigma_x.\sigma_y.Corr(X, Y)} \tag{4.4.1}$$

As long as the asset are perfectly positively correlated, meaning $Corr(X, Y) = 1$, the right-hand side of the equation simplifies to weighted average of standard deviations (see Equation 4.5.1)

$$\sigma_p = (w_1 * \sigma_x + w_2 * \sigma_y) \tag{4.5.1}$$

If $Corr(X, Y) = -1$, i.e. if the assets are perfectly negatively correlated, the portfolio's standard deviation is given by the Equation (4.6.1).

$$\sigma_p = |w_1 * \sigma_x - w_2 * \sigma_y| \tag{4.6.1}$$

For uncorrelated assets, i.e. when $Corr(X,Y) = 0$, the standard deviation has the form of Equation 4.7.1.

$$\sigma_p = \sqrt{w_1^2.Var(X) + w_2^2.Var(Y)} \tag{4.7.1}$$

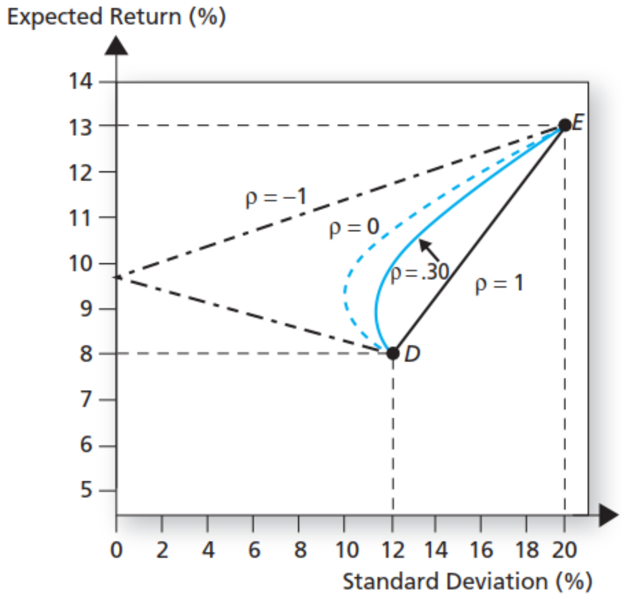

Figure 4.3: benefit of diversification (Bodie et al., 2013)

Generally speaking, as long as the assets are not perfectly positively correlated, i.e. $Corr(X,Y) =< -1; 1)$, the portfolio standard deviation is less than the weighted average of the standard deviations of the underlying assets for given expected return. As shown before, the expected return of a portfolio is unaffected by correlation between the underlying assets but portfolio's standard deviation can be lowered. Therefore, assets with non-perfect correlation offer some degree of diversification benefit in sense that for the same expected return the standard deviation of the portfolio can be lowered.

Using the Figure 4.3 we can see the benefits of diversification graphically. Let's consider two risky assets which should build our portfolio where $E(r_1) = 8\%, SD(r_1) = 12\%, E(r_2) = 13\%, SD(r_2)$. An expected return between 8 % and 13 % can be reached by choosing the right weights of those two assets. However, as Figure 4.3 shows the lower the correlation between those two assets the lower portfolio standard deviation can be reached. Therefore, the most optimal way to create a portfolio is to include assets which are perfectly negatively correlated.

In such case, it would be possible to reach a certain rate or return which would be close to 10%.

4.7 Risk free asset

Risk free asset is an asset which yields a certain return for every outcome. Typically, a yield on government bond is considered a risk-free rate as the returns are backed by the government which issued the bond. Consequently, the variance of such asset is zero. It is useful the know the risk-free rate in order to be able to determine the Sharpe ratio. This measure helps to derive the risk-adjusted return. It can be calculated using the Equation 4.8.1.

$$Sharpe\ ratio = \frac{Return\ of\ portfolio - risk\ free\ rate}{standard\ deviation\ of\ asset's\ excess\ return} \tag{4.8.1}$$

where the expression in the numerator is called risk premium, representing the excess return of the underlying portfolio over the risk-free rate. Generally, investor prefer portfolios with higher SR which gives him better trade-off between risk and return.

4.8 Modern portfolio theory

The Modern Portfolio Theory, also referred to as mean-variance analysis, was introduced by the economist Harry Markowitz (Markowitz, 1952). For this contribution to the world of finance he was awarded a Nobel Prize. MPT is widely used for asset allocation. This theory explains how to construct portfolios which maximize the expected return for given level of risk. It emphasizes that low risk and high return are two contradicting goals in the sense that investments with higher expected return usually are more volatile which implies higher risk.

The main assumptions used by Markowitz are:

1) Investors are rational, always trying to maximize return while minimizing the risk
2) Investors are willing to face additional risk if they compensate with higher expected return
3) Investors can borrow and lend unlimited amount of money at risk-free rate
4) Efficiency of markets
5) No taxes and transaction costs

6) All investors have access to all relevant information for making an investment decision

Furthermore, Markowitz argues that diversification is beneficial. The key idea is that holding portfolio consisting of several different assets can be less risky than holding a portfolio consisting of only one asset. It turns out that such diversification allows investor to reach the same rate of expected return while facing lower risk. When finding the optimal portfolio, it is important to determine how the particular asset contributes to the risk of the overall portfolio rather than the riskiness of that individual asset. In this research we will use approach which is based on historical data. This will be used to analyze possible future development which might however be quite different from the past. Generally, we assume that investors try to maximize their returns for given level of risk they are bearing. Also, it is assumed that investors are generally risk-averse, meaning that investors prefer a less risky portfolio to the risky one.
The MPT was further developed by the Capital Asset Pricing Model introduced independently by Sharpe, Treynor, Lintner and Mossin in the 1970s (Mangram, 2013).

Generally, the procedure of finding the optimal portfolio consists of several steps briefly demonstrated in Figure 4.4.

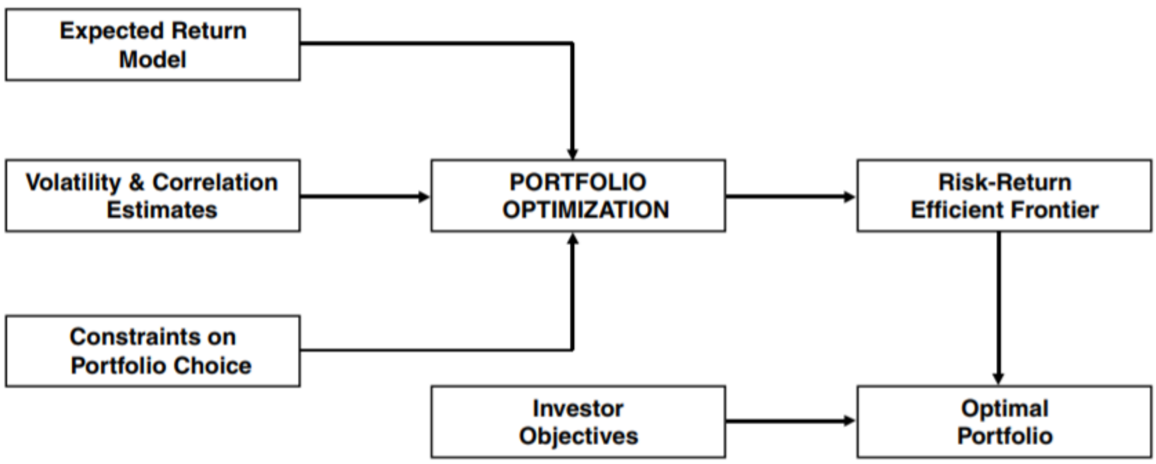

Figure 4.4: Fabozzi, Gupta, & Markowitz (2002)

4.8.1 Efficient frontier

First, the assets which should build our portfolio and their expected return together with their variance should be determined. Given the information about their expected return and variance a rational investor trying to maximize his return for given level of risk is able to build a so-called frontier by using different combinations of assets' weights. This is a set of optimal portfolios which offer the highest expected return for given level of risk. Put differently, it is a set of portfolios with lowest possible risk for given expected return. That is why a rational investor should always invest in a portfolio which lies on this efficient frontier. In Figure 4.5 the situation is shown graphically. The blue triangles represent the individual assets which build our final portfolio and which are used to create the efficient frontier where the efficient portfolios lie. The part of the frontier lying above the minimum variance portfolio is called efficient while the remaining part is inefficient.

The red square represent the inefficient portfolios. Those are such portfolios which lie either to the right of the frontier or directly on the inefficient part of the frontier. The label "inefficient" comes from the fact that it is possible to find alternative portfolios which offer higher expected rate of return for the same risk or lower risk for the same rate of expected return.

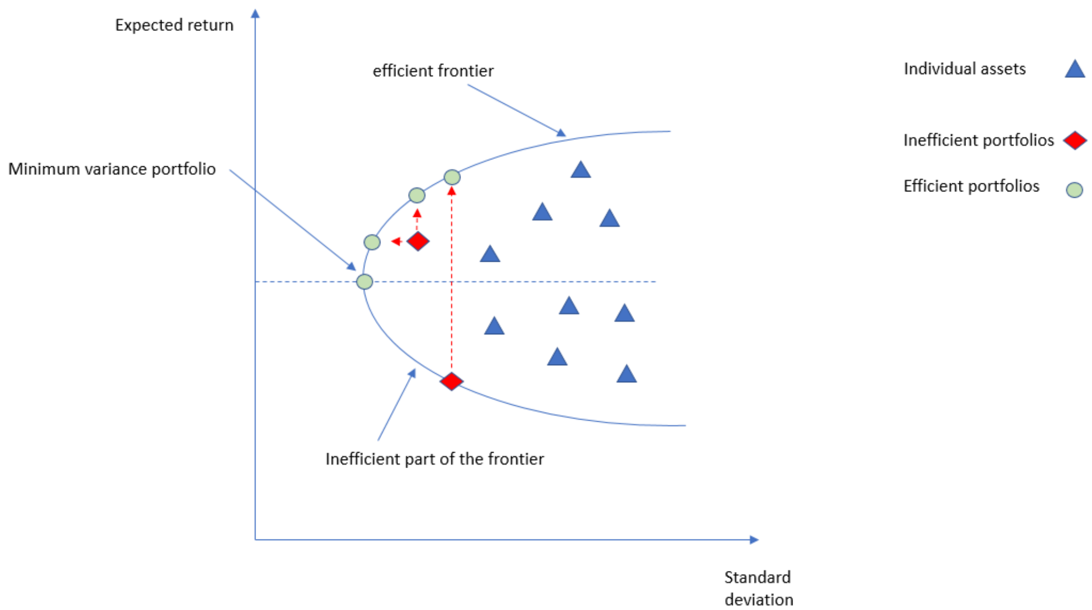

Figure 4.5: efficient frontier[65]

[65] Author's own plot

The optimal portfolio is the portfolio which gives the investor the highest utility. Figure 4.6 shows the situation for two different sets of indifference curves each for investor A and B with different level of risk aversion.

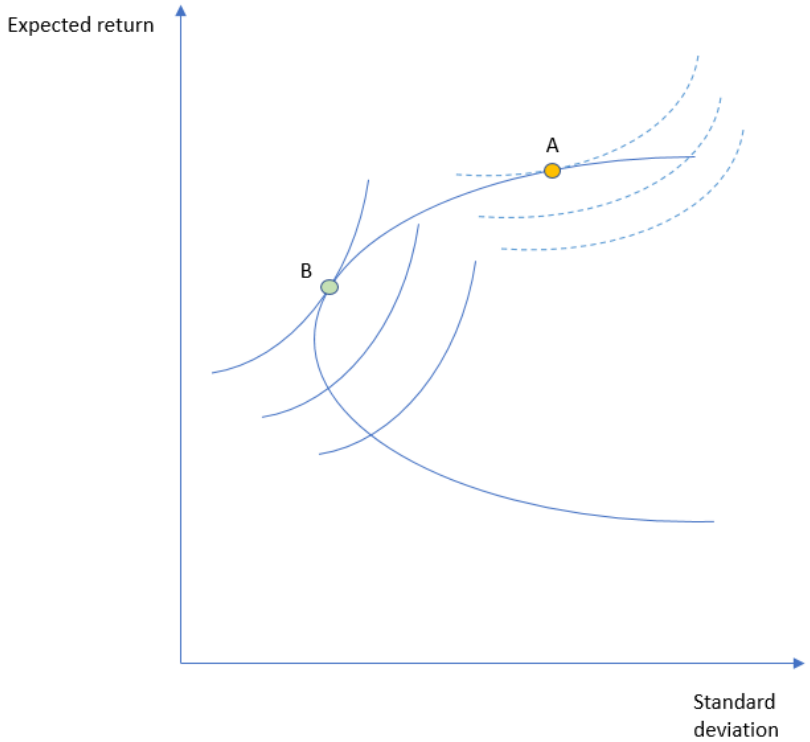

Figure 4.6: optimal portfolio without risk-free asset [66]

The situation changes when we let the risk-free asset to be a part of the portfolio. In such case we combine an efficient portfolio p found in the way described above and the risk-free asset. We can denote this newly created portfolio by letter q. The expected return and the standard deviation of such portfolio q are given by Equations 4.9.1 and 4.1.2.

$$\mu_q = w * \mu_p + (1 - w) * r_f = r_f + w * (\mu_p - r_f) \tag{4.9.1}$$

$$\sigma_p = \sqrt{w^2 * \sigma_p^2 + (1 - w)^2 * \sigma_{rf}^2 + 2 * w * (1 - w) * cov(\mu_p, r_f)} = w * \sigma_p \tag{4.1.2}$$

where

[66] Author's own plot

$\mu_q = the\ expected\ return\ of\ portfolio\ q$

$\mu_p = the\ expected\ return\ of\ portfolio\ p$

$w = the\ weight\ of\ portfolio\ p$

$r_f = risk\ free\ rate$

Hence, the expected return of this portfolio can also be written using the Equation 4.2.2.

$$\mu_p = r_f + \frac{\sigma_q}{\sigma_p} * (\mu_p - r_f) \tag{4.2.2}$$

This expression is called the Capital allocation line. Depending on the choice of the efficient portfolio which should build our final portfolio q the CAL have different slope. The investor tries to find a portfolio with the highest Sharpe ratio because such portfolio gives him the best relationship between risk and return. As Sharpe ratio corresponds to the slope of the CAL investor should find the steepest CAL. In Figure 4.7 this efficient portfolio corresponds to the point C which results in the highest SR compared to all other efficient portfolios. It is called tangency portfolio.

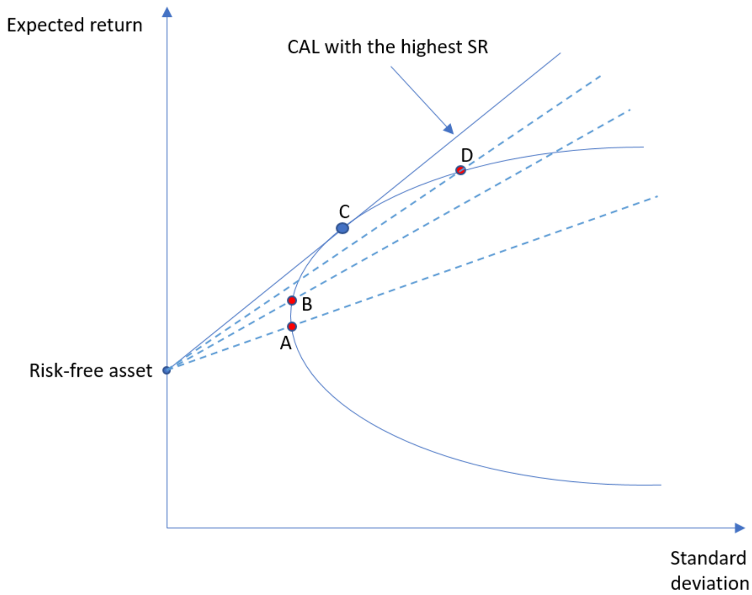

Figure 4.7: searching for the steepest CAL[67]

The portfolio q therefore lies somewhere on the CAL corresponding to the highest SR. The final optimal portfolio depends on the preferences of the investor. As the Figure 4.7 shows, if

[67] Author's own plot

the risk-free asset is available the investor is generally better-off as he can reach portfolio which brings him higher utility (See Figure 4.8).

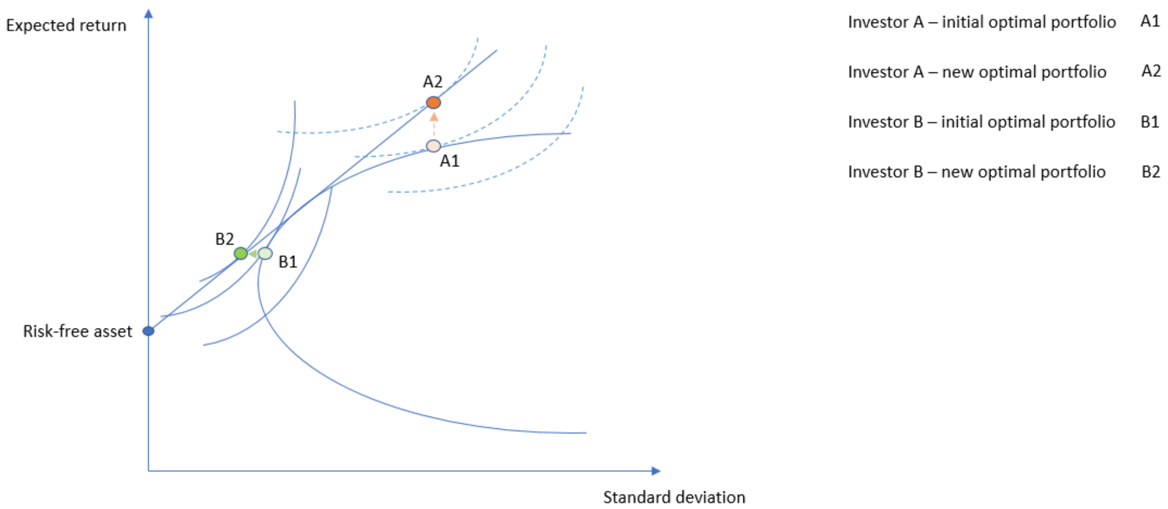

Figure 4.8: optimal portfolio with risk-free asset[68]

The important conclusion is that regardless of the risk aversion the optimal portfolio of every investor consists of the tangency portfolio and the risk-free asset. The only difference between two optimal non-identical portfolios is in the weights of the tangency portfolio and the risk-free asset. The more risk-averse the investor is the bigger will be the share of his portfolio invested in the risk-free asset.

Hence, the conclusion is that the process of finding the optimal investor consists of two steps. First, the efficient frontier is build and the optimal risky is found. In the second step, the optimal portfolio is found based on investor's preferences. This result is called a separation property, first noted by the Nobel laureate by Tobin (1958).

4.8.2 Finding the minimum variance portfolio

For a risk averse investor who would like to minimize the risk he should bear, the minimum variance portfolio should be found. In order to find such portfolio consisting of N assets, we must solve the following optimization problem:

$$min_w w^T * C * w \;\; s.t. \sum_{i=1}^{N} w_i = 1 \tag{4.3.2}$$

[68] Author's own plot

where

$w\ is\ the\ N \times 1\ matrix\ consisting\ of\ assets' weights$

$C\ \ is\ the\ N\ \times N\ variance - covariance\ matrix$

$w^T\ is\ the\ 1\ \times N\ matrix\ created\ by\ transposing\ the\ matrix\ w$

the $N\ \times 1$ matrix consisting of the weights which minimize the variance of the portfolio (and therefore the standard deviation as well) can be obtained by equation (4.4.2)

$$w = \frac{C^{-1} * I}{I^T * C^{-1} * I} \tag{4.4.2}$$

where

$C^{-1} is\ the\ N \times N\ inverse\ matrix\ of\ the\ variance - covariance\ matrix\ C$

$I\ is\ the\ N \times 1\ matrix\ with\ all\ its\ elements\ equal\ to\ 1$

$I^T is\ the\ 1 \times N\ matrix\ created\ by\ transposing\ the\ matrix\ I$

4.8.3 MPT today

Even though the theory generated little interest initially, the ideas of the MPT have been widely adopted by the finance sector. According to Fabozzi, Gupta, & Markowitz (2002), even several years later, at the beginning of the 21st century, there are financial models based on the MPT incorporating new findings.

Chi, Ding, & Peng (2019) note that the mean-variance model of Markowitz is still widely used for portfolio selection and risk management. The model has been intensively used in the areas of asset allocation, portfolio management and portfolios construction. Furthermore, this model has been extended to other models such as mean-downside risk model, mean-VaR model or mean-CVaR model. Researchers also try to obtain more practical ways of asset allocation. For instance, Li, Chan, & Ng (1998) deal with the problem of asset allocation using mutli-period model.

4.8.4 Critics

Nevertheless, the modern portfolio theory has some drawbacks. The analysis is based on historical data. However, the future might be quite different from what we experienced in the past. Also, we might arrive at different result when analyzing different periods in the past. The next problem is that when the number of assets being analyzed is big, the number of estimations needed to be made in order to fill the variance-covariance matrix is quite large. In order to analyze N assets, we need N estimates of the expected return, N estimates of the variance and $\frac{(N^2-N)}{2}$ estimates of covariances. Another problem is that inconsistency of correlation estimates can lead to nonsensical results, such as negative variance of the overall portfolio (Bodie et al., 2013)

MPT and the efficient frontier are based on some assumptions which might not hold. (Mangram, 2013) argues that in reality the assumption about the perfect information for all investors does not hold and information asymmetry is a problem. Also, it is not possible for investors to lend and borrow without a limit for a risk-free rate. Clearly, the taxes and other transaction costs do exist in reality which violates one of the assumptions. As (Curtis, 2004) points out, investors are not always rational, trying to maximize their wealth.

5. Empirical part

5.1 Description of data

In this research data about loans on Zonky were analyzed. This data was provided by Zonky itself. It includes information about 46229 loans in total for a period starting in 2015, when Zonky was founded, and ending in Mai 2019. Since its foundation more than six and half billion CZK have been lent to the loan applicants from the Czech Republic. Each loan is assigned to one of the eleven interest rates which represents the level of riskiness the associated with that particular loan as described earlier. There are three risk categories which have been introduced recently - at the beginning of 2019. These correspond to the interest rates 2,99%, 6,99% and 9,49%.

When analyzing the data, we can see that most of the loan sizes were smaller than 200 000 CZK which supports the idea that most of the P2P loans are microloans (see Figure 5.1). By examining the purpose of the loan, we find that the funds obtained are mostly used for debt refinancing, household and purchase of vehicle as claimed by the borrowers. These three categories make up more than 70 percent of all loans provided by Zonky. This is similar to the US P2P company Lending club[69]. It is also consistent with the most popular ways of using the obtained funds at Zopa platform. Among these are: purchase of a new car, paying off credit cards, loan consolidation or wedding costs[70].

Only around 16 percent of the borrowers decided to get insured against their insolvency. Interestingly, we found that in some cases loan default was eventually profitable for the investors. This is due to the fact, that the penalty collected by Zonky for being late with payments is shared among the investors. In some cases, the profit from this penalty was eventually higher than the profit from the interest payments which are traditionally the main kind of revenue for investors.

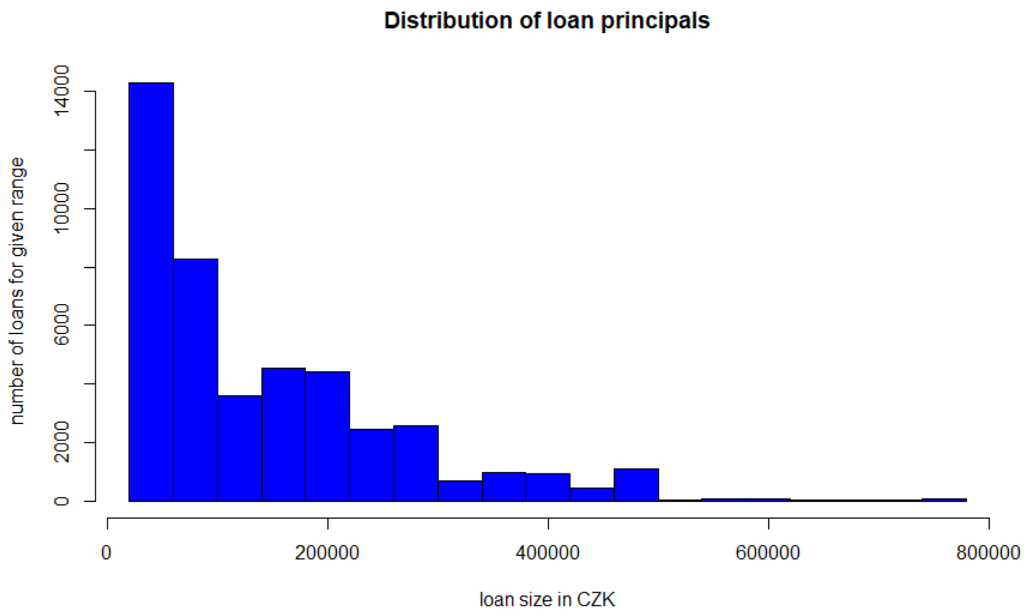

Figure 5.1: Distribution of loan principals

[69] "Statistics", LendingClub, retrieved May 1, 2019 from https://www.lendingclub.com/info/statistics.action

[70] "What can I use a Zopa loan for?", Zopa, retrieved May 1, 2019 from http://help.zopa.com/customer/portal/articles/2468041

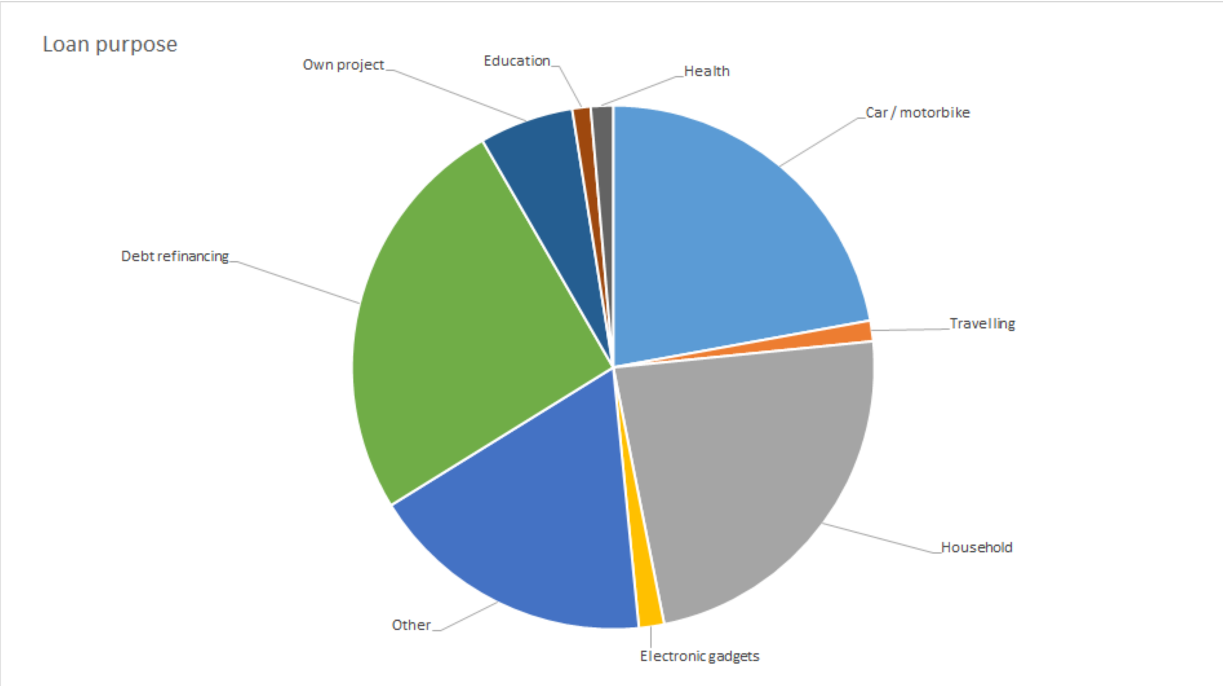

Figure 5.2: loan purpose

There are three kinds of loans in total. The first category of loans is denoted as PAID. It is a category for loans which have been fully repaid. This means there is no principal and interest payments remaining unpaid. PAID OFF stands for loans which have been declared by Zonky to be in default. This implies that part of the debt remains unpaid. Often some part of the remaining debt has been collected. The last category is ACTIVE. This stands for loans which are currently outstanding.

Table 5.1: basic information

status	*loan count*	*share*	*sum of amount credited*	*share*
active	34871	75,4 %	5 433 582 000	80,3 %
paid	10572	22,9 %	1 244 908 000	18,4 %
defaulted	786	1,7 %	86 777 000	1,3 %
SUM	46229	100 %	6 765 267 000	100 %

Table 5.2: current days past due for active and defaulted loans

current days past due								
1-30	*31-60*	*61-90*	*91-120*	*120-180*	*180-360*	*360-720*	*720+*	*Sum*
499	220	129	77	141	329	271	30	1696

There is also a piece of information regarding the length of a particular contract. This have different meaning for each of the three loan categories. For PAID loans it states the actual term the loan was outstanding which might be less than the agreed term due to early repayment. In case of PAID OFF loans this number stands for the time when the loan defaulted. More specifically, this time is shown as the number of months after the loan was provided.

5.2 Methodology

In this paper we will use the so-called rating-based model. Guo et. al (2015) describes it as a model which assumes that every loan from the same risk category bears the same level of risk. Such models have been widely used by the financial institutions because of its practicality. Our goal is to use the MPT to find the optimal portfolio. It is necessary to make some adjustments in order make the MPT applicable. First, the expected return of loans will be derived using different scenarios for possible future performance as well as covariance between loans. After that, we will do the optimization process for each scenario. We will consider taxes and fees in order to obtain more realistic results. However, we will not apply any discounting for the sake of simple comparison of investments. Therefore, we will only consider the nominal value of all payments. In case of Zonky, the assets which build the investors' investment portfolio are represented by loans. However, P2P providers, including Zonky, generally do not allow to have a short position. Hence, in this analysis the author will restrict himself to the portfolio consisting of assets with positive or zero weights (Equation 5.1)

$$w_i > 1, i = 1 \ldots\ldots N \tag{5.1}$$

where N is equal to number of assets

In case of investing in loans on Zonky platform. The number of assets will be equal to the number of interest rates which will be also called risk categories. Because the risk categories corresponding to the interest rates 2,99%, 6,99% and 9,49% have been introduced just recently, there are no historical data available for them. Therefore, we will consider them in our analysis. Furthermore, we will consider a risk-free asset in our analysis. This will be the rate on a saving account offered by the Trinity bank[71] with interest rate equal to 1,18%. The reason why we consider it to be risk-free is that the deposits are insured up to a limit of 100 000 EUR. Consequently, the standard deviation of this investment is zero.

5.3 Measuring the returns

One of the broadly used concepts to measure the performance of an investment is the so-called return on investment. It measures return on a particular investment relative to the costs of making that investment. The formula used to determine ROI is given by the Equation 5.2.

$$ROI = \frac{current\ value\ of\ investment - cost\ of\ investment}{cost\ of\ investment} \tag{5.2}$$

We will use ROI to calculate returns for the all three kinds of loans provided on Zonky's platform under certain assumptions. This is the same approach as used by Polák (2017) or Singh, Gopal, & Li (2008).

To take into account differences in the terms of individual loans we will annualize the returns. This also enable us to compare the returns earned. The Equation 5.3 is used for annualizing.

$$annualized\ returns = (1 +\ ROI)^{\frac{12}{number\ of\ months\ held}} - 1 \tag{5.3}$$

where days held represents the total number of days the loan was outstanding meaning the total length of the period between the date when the loan was credited and the date when it was fully repaid or when it was considered defaulted due to failure of the borrower to repay his loan according to agreed terms.

If loan is labeled as PAID it means that the whole debt was repaid. In such case the ROI will be derived using Equation 5.4.

$$ROI = 0{,}85\,.(interest\ rate - investor's\ fee) \tag{5.4}$$

[71] Trinity banka, retrieved May 1, 2019 from https://www.trinitybank.cz/lide-sporici-ucty-vyhoda-plus/

where the interest rate corresponds to the interest rate applied on the loan and the investment fee is expressed in %, set according to Zonky's policy. In order to account for taxes, the sum of these terms is multiplied by 0,85 which corresponds to the tax rate of 15 %. Even though the fee policy changed in September 2017, we apply the current fees even in months before there was a change. The ROI for PAID loans will not be annualized.

In case of PAID OFF loans the following formula is used for ROI (see Equation 5.5)

$$ROI = \frac{(paid\ interest + paid\ principal + penalty + expected\ RR) - (tax + \ fee + principal)}{fees + principal + tax} \tag{5.5}$$

where

$paid\ interest = the\ part\ of\ interest\ payments\ paid\ by\ the\ borrower\ so\ far$

$paid\ principal = the\ part\ of\ the\ principal\ paid\ by\ the\ borrower\ so\ far$

$penalty = penalty\ paid\ by\ the\ borrower\ for\ being\ late\ on\ payment\ obligations$

$expected\ recovery\ rate$
$= the\ part\ of\ the\ remaining\ debt\ which\ we\ expect\ to\ be\ paid\ back$

$fee = the\ sum\ of\ the\ investment\ fees\ paid\ by\ investors$

$principal = initial\ loan\ principal$

For the sake of clarity, we briefly discuss the important dates we will be working with in our analysis of the PAID OFF loans. These dates are shown on a time axis. The axis starts with the date when the loan was made by the platform. We assume that the payments had been made according to the agreed terms until the date labeled as "no more payments". After some time (without any payments from the debtor) the loan was declared to be in default. The current number of days past due is the difference between today (May 2019) and the date when the debtor stopped making payments.

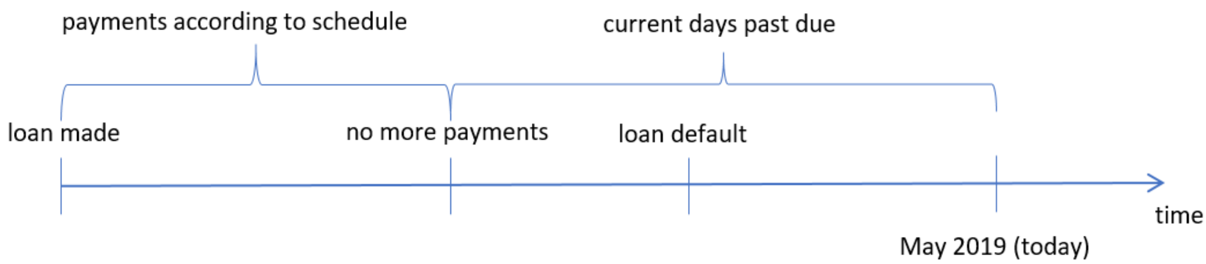

Figure 5.3: important days[72]

The amount of principal and interest collected before the debtor stopped making regular payments can be estimated by the loan amortization schedule. The installment amount which can be seen from the data constitutes not only of the repayment of principal and interest payments but also from the borrower's fee and the insurance if the debtor decided to have it. Therefore, it does not exactly reflect the amount received directly by the investors each month. Hence, we will try to estimate this monthly amount using the annuity formula (see Equation 5.6)

$$installment = n * \frac{\frac{p}{12} * \left(1 + \frac{p}{12}\right)^t}{\left(1 + \frac{p}{12}\right)^t - 1} \tag{5.6}$$

where:

$n = loan\ principal$

$p = annual\ interest\ rate\ paid\ by\ the\ debtor$

$t = number\ of\ monthly\ payments\ in\ total$

This installment, received each month by the investor (given by equation), includes the interest payments as well as part of the principal. First, the interest payment is made (remaining principal multiplied by the respective interest rate). The remaining amount (installment – interest payment) is than used for repayment of a part of the remaining principal. The process continues until the debt is fully repaid (see Table 5.3).

[72] Author's own figure

Table 5.3: loan amortization schedule, principal = 100 000 CZK, term = 12 months, interest rate = 19,99%[73]

month	installment	paid interest	paid principal	remaining principal
1	9 262,97	1 665,83	7 597,14	92 402,86
2	9 262,97	1 539,28	7 723,69	84 679,17
3	9 262,97	1 410,61	7 852,36	76 826,81
4	9 262,97	1 279,81	7 983,17	68 843,64
5	9 262,97	1 146,82	8 116,15	60 727,49
6	9 262,97	1 011,62	8 251,35	52 476,14
7	9 262,97	874,17	8 388,81	44 087,33
8	9 262,97	734,42	8 528,55	35 558,78
9	9 262,97	592,35	8 670,62	26 888,16
10	9 262,97	447,91	8 815,06	18 073,10
11	9 262,97	301,07	8 961,90	9 111,19
12	9 262,97	151,78	9 111,19	0,00

The investment fees for PAID OFF loans will be derived differently than for PAID loans. As already mentioned, the fee is always derived from the remaining part of the principal being currently invested. Based on the annuity formula we can estimate the loan amortization schedule. This will give us the remaining principal for each month which will be then used for the calculation of the investment fee for each month. Generally, the sum of all fees for t months after the loan was issued is given by Equation 5.7.

$$sum\ of\ investor's\ fees\ = \sum_{i=1}^{t} P_i * \frac{30}{360} * fee, \qquad for\ t \leq N, \tag{5.7}$$

$$P_i = \begin{cases} loan\ initial\ principal\,, & for\ i = 1 \\ P_{i-1} - \left(L * \dfrac{\frac{IR}{12} * \left(1 + \frac{IR}{12}\right)^N}{\left(1 + \frac{IR}{12}\right)^N - 1} - \dfrac{IR}{12} * P_{i-1} \right), & for\ i = 2 \ldots t \end{cases}$$

where

$t =$ number of months (after the loan was issued)

$N = term\ contracted$

[73] Author's own calculation based on equation

$fee = annual\ investment\ fee\ in\ \%\ paid\ by\ investors$

$IR = annual\ interest\ rate\ applied\ in\ the\ particular\ loan$

$L = loan\ principal$

The period t is equal to the length of the period in months before the loan was declared to be in default (see Figure 5.4) This total fee amount will be calculated for every PAID OFF loan using VBA.

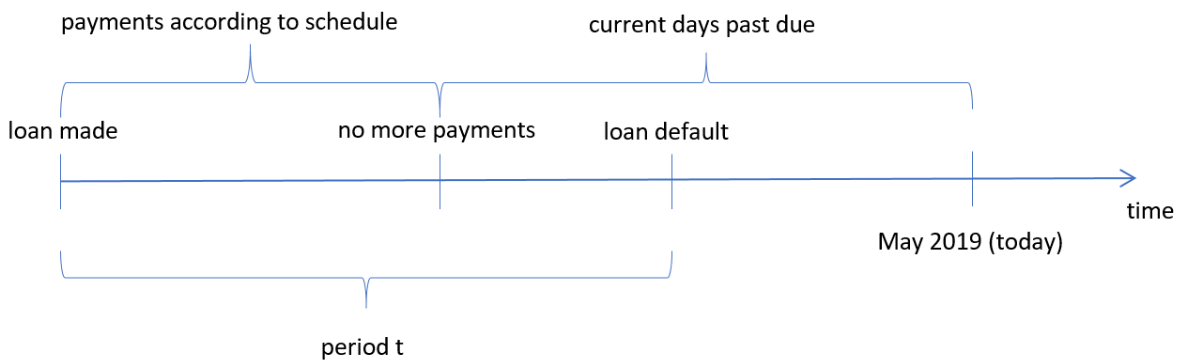

Figure 5.4: period t[74]

Zonky does not provide any information about the average recovery rate or the average length of recovery operations. Hence, we will assume three different scenarios.
The worst-case scenario is that from now on no parts of the remaining debt will be collected anymore. The reasoning behind this assumption is that there is no guarantee that the remaining part of the debt will be collected as Zonky is not obliged to do so. This scenario is rather pessimistic.

For the second scenario we will use the information obtained at Prosper. According to its statistics, investors receive around 8% of the charge-off principal[75]. Therefore, we will assume that 8% will be the part of the charge-off principal and interest payments which will be successfully collected from the debtor in total. If the debtor has already paid more than those 8 % since he has defaulted on his loan we will assume that he will not make any additional payments.

[74] Author’s own figure
[75] “Prosper Performance Update: January 2017”, Prosper, retrieved April 10, 2019 from https://www.prosper.com/about-us/wp-content/uploads/Performance_Update_January2017.pdf

The best-case scenario is that on average 46% of the remaining principal and interest will be successfully collected in total. This corresponds to the average recovery rate at Bondora between 2014 and 2017[76]. If the debtor has already paid more than those 46 % since he has defaulted on his loan we will assume that he will not make any additional payments.

In the second and the third case we assume that the given estimated amount will be collected (if any) only if the loan is currently no more than 2 years (720 days) past due. We assume that if the loan is currently more than 2 years overdue the chances that additional amount will be collected is very small and therefore nothing more will be collected. Furthermore, we assume that If the loan is currently less than 720 days past due then the given estimated amount of the charge-off principal and the interest payments will be collected in the middle of the period which starts on the 1st May 2019 and ends 720 days after the debtor stopped making payments (denoted by a dot in figure).

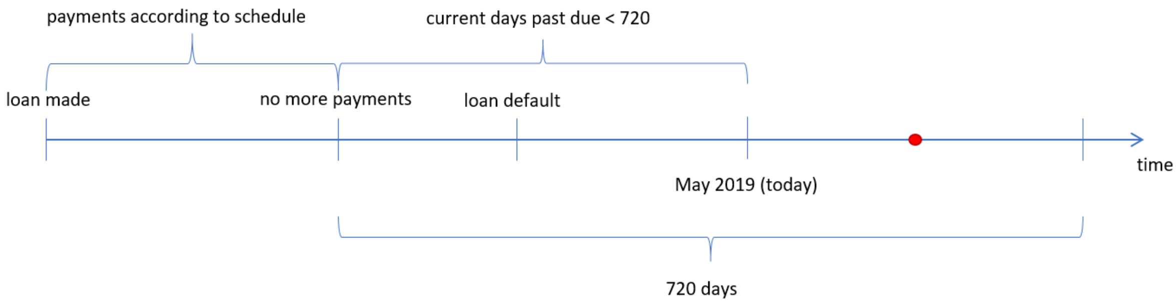

Figure 5.5: time of final repayment for defaulted loans [77]

For calculation of taxes we will again use the estimated loan amortization schedule (see table) We assume that before the debtor stopped making payments the payments had been made according to the schedule. The difference between the interest payments (representing the source of investor's profit) received by the investor before the debtor stopped making payments and investor's fees (representing his costs) paid by the investor over period t is subject to the tax rate of 15 %. Any collected charged off interest payments are not subject to tax as these do not represent any profit but only reduce the remaining debt.

[76] Bondora, retrieved April 11, 2019 from https://www.bondora.com/blog/average-recovery-rate-for-2014-2017-is-46-percent/
[77] Author's own figure

In our analysis we will not consider the ACTIVE loans.

After calculating the (annualized) return for each PAID and PAID OFF loan we will calculate the average (annualized) ROI for all PAID and PAID OFF loans credited in each consequent month between March 2016 and February 2019 (we will use months in which at least 1 loan from each risk category was granted). This gives us 36 monthly-averages for each risk category. We will take the weighted average of these monthly averages for each risk category. In order to obtain the variance-covariance matrix we will use matrix algebra and the excel array functions. First, the $n\ x\ m$ excess return matrix X will be created where n stands for the number of observed months (36) and m is the number of categories which is 8 in this analysis. In matrix X, from each element the respective weighted average will be subtracted. After that we create another $m\ \times m$ matrix T:

$$T = X^T * X$$

Finally, the $m \times m$ VCM is than created by dividing every element of matrix T by n. The VCM will provide us with the necessary inputs for the optimization.

Because we restricted ourselves only to defaulted and paid loans made between March 2016 and February 2019 our analysis uses data about 11045 loans.

6. Results

6.1 Statistical properties

6.1.1 The worst-case scenario

We will start with the worst-case scenario expecting that no part of the outstanding debt will be repaid anymore. The average ROI for each of the series of months can be seen in Table 6.1.

Table 6.1: Average ROI for given month and interest rate – the worst-case scenario

	Interest rate							
month credited	*3,99%*	*4,99%*	*5,99%*	*8,49%*	*10,99%*	*13,49%*	*15,49%*	*19,99%*
01.03.2016	3,2%	3,8%	4,2%	4,8%	5,6%	6,9%	3,7%	5,1%
01.04.2016	3,2%	3,8%	2,6%	5,3%	6,3%	6,4%	-3,7%	-2,8%
01.05.2016	3,2%	3,8%	3,3%	5,3%	5,1%	7,5%	7,5%	5,7%
01.06.2016	3,2%	3,8%	4,2%	4,4%	5,4%	8,5%	8,4%	7,1%
01.07.2016	3,2%	3,8%	4,2%	1,6%	4,3%	4,7%	5,9%	-1,1%
01.08.2016	3,2%	3,8%	2,5%	5,3%	3,6%	4,4%	1,5%	7,9%
01.09.2016	3,2%	3,8%	4,2%	4,3%	4,5%	8,5%	5,0%	-8,6%
01.10.2016	3,2%	3,8%	4,2%	4,1%	1,7%	4,9%	4,5%	8,0%
01.11.2016	3,2%	3,8%	3,3%	4,3%	4,1%	7,7%	-1,0%	-1,7%
01.12.2016	3,2%	3,8%	4,2%	4,1%	1,8%	1,9%	0,8%	-7,5%
01.01.2017	3,2%	3,8%	2,7%	5,3%	5,1%	4,8%	-2,3%	8,9%
01.02.2017	3,2%	3,8%	4,2%	5,3%	5,3%	4,7%	2,8%	1,9%
01.03.2017	3,2%	3,8%	3,0%	0,7%	5,0%	7,3%	2,6%	-2,5%
01.04.2017	3,2%	3,8%	2,5%	3,6%	-2,9%	-20,6%	6,8%	-4,4%
01.05.2017	3,2%	3,8%	0,3%	-1,3%	2,3%	1,9%	-3,7%	-4,8%
01.06.2017	3,2%	3,8%	2,3%	1,9%	0,8%	-5,8%	-8,1%	-8,6%
01.07.2017	1,0%	3,8%	1,6%	0,8%	-1,3%	-5,2%	-6,9%	6,9%
01.08.2017	3,2%	1,6%	1,6%	0,6%	-3,0%	1,0%	-15,0%	6,2%
01.09.2017	3,2%	2,6%	2,5%	-0,6%	-0,5%	2,5%	-4,0%	-6,9%
01.10.2017	3,2%	1,6%	4,2%	0,3%	-1,3%	-2,9%	-4,9%	-14,9%
01.11.2017	-0,4%	3,8%	3,7%	-0,8%	2,9%	-1,1%	-4,0%	-9,0%
01.12.2017	-0,2%	3,8%	2,6%	-0,3%	-1,5%	-5,6%	-3,5%	-2,7%
01.01.2018	-5,0%	2,1%	2,8%	2,0%	-3,4%	-5,1%	-3,6%	-7,3%
01.02.2018	3,2%	2,3%	2,3%	3,2%	-0,6%	-3,4%	-0,5%	-16,0%
01.03.2018	3,2%	3,8%	3,2%	-4,2%	-1,7%	-3,6%	-11,8%	0,5%
01.04.2018	3,2%	3,8%	3,2%	2,0%	-1,5%	0,2%	-10,2%	-5,5%
01.05.2018	3,2%	1,7%	2,3%	2,2%	-1,0%	-6,0%	-5,8%	-4,3%
01.06.2018	3,2%	3,8%	3,2%	2,6%	-2,4%	-3,1%	-1,7%	-3,6%
01.07.2018	3,2%	3,8%	0,8%	1,9%	-1,6%	-2,6%	5,8%	4,1%
01.08.2018	3,2%	3,8%	1,3%	2,2%	2,5%	5,8%	0,6%	5,0%
01.09.2018	3,2%	3,8%	4,2%	5,3%	6,8%	0,4%	-4,4%	-26,5%
01.10.2018	3,2%	3,8%	0,0%	3,1%	2,1%	4,0%	5,7%	5,7%
01.11.2018	3,2%	3,8%	4,2%	3,4%	1,6%	1,3%	9,8%	2,5%
01.12.2018	3,2%	3,8%	4,2%	2,7%	6,8%	8,5%	9,8%	-15,4%
01.01.2019	3,2%	3,8%	4,2%	5,3%	2,8%	8,5%	9,8%	12,7%
01.02.2019	3,2%	3,8%	4,2%	5,3%	6,8%	8,5%	9,8%	12,7%

weighted average	**2,4%**	**3,3%**	**2,8%**	**1,8%**	**0,9%**	**0,1%**	**-1,7%**	**-1,9%**

Table 6.2: excess return matrix – the worst-case scenario

	Interest rate							
month credited	*3,99%*	*4,99%*	*5,99%*	*8,49%*	*10,99%*	*13,49%*	*15,49%*	*19,99%*
01.03.2016	0,82%	0,52%	1,48%	2,93%	4,68%	6,80%	5,39%	6,97%
01.04.2016	0,82%	0,52%	-0,16%	3,52%	5,34%	6,28%	-1,98%	-0,95%
01.05.2016	0,82%	0,52%	0,50%	3,52%	4,15%	7,36%	9,26%	7,58%
01.06.2016	0,82%	0,52%	1,48%	2,59%	4,52%	8,39%	10,14%	8,97%
01.07.2016	0,82%	0,52%	1,48%	-0,25%	3,35%	4,61%	7,58%	0,77%
01.08.2016	0,82%	0,52%	-0,27%	3,52%	2,70%	4,30%	3,17%	9,80%
01.09.2016	0,82%	0,52%	1,48%	2,45%	3,58%	8,39%	6,74%	-6,73%
01.10.2016	0,82%	0,52%	1,48%	2,28%	0,78%	4,81%	6,23%	9,85%
01.11.2016	0,82%	0,52%	0,55%	2,52%	3,22%	7,60%	0,76%	0,19%
01.12.2016	0,82%	0,52%	1,48%	2,27%	0,92%	1,77%	2,53%	-5,60%
01.01.2017	0,82%	0,52%	-0,03%	3,52%	4,16%	4,74%	-0,61%	10,75%
01.02.2017	0,82%	0,52%	1,48%	3,52%	4,40%	4,62%	4,51%	3,82%
01.03.2017	0,82%	0,52%	0,22%	-1,12%	4,11%	7,17%	4,33%	-0,66%
01.04.2017	0,82%	0,52%	-0,21%	1,74%	-3,78%	-20,69%	8,54%	-2,53%
01.05.2017	0,82%	0,52%	-2,45%	-3,17%	1,37%	1,76%	-1,98%	-2,93%
01.06.2017	0,82%	0,52%	-0,41%	0,04%	-0,13%	-5,88%	-6,39%	-6,71%
01.07.2017	-1,38%	0,52%	-1,12%	-1,05%	-2,24%	-5,31%	-5,18%	8,80%
01.08.2017	0,82%	-1,67%	-1,13%	-1,21%	-3,93%	0,87%	-13,26%	8,06%
01.09.2017	0,82%	-0,68%	-0,28%	-2,47%	-1,45%	2,37%	-2,23%	-4,99%
01.10.2017	0,82%	-1,71%	1,48%	-1,49%	-2,17%	-3,05%	-3,16%	-12,98%
01.11.2017	-2,78%	0,52%	0,91%	-2,58%	1,98%	-1,19%	-2,31%	-7,07%
01.12.2017	-2,65%	0,52%	-0,19%	-2,14%	-2,43%	-5,74%	-1,79%	-0,79%
01.01.2018	-7,44%	-1,18%	0,08%	0,22%	-4,28%	-5,23%	-1,89%	-5,43%
01.02.2018	0,82%	-1,05%	-0,49%	1,38%	-1,51%	-3,55%	1,26%	-14,10%
01.03.2018	0,82%	0,52%	0,48%	-6,03%	-2,63%	-3,69%	-10,04%	2,40%
01.04.2018	0,82%	0,52%	0,47%	0,15%	-2,42%	0,09%	-8,44%	-3,65%
01.05.2018	0,82%	-1,60%	-0,48%	0,35%	-1,94%	-6,10%	-4,11%	-2,41%
01.06.2018	0,82%	0,48%	0,46%	0,80%	-3,32%	-3,17%	0,07%	-1,71%
01.07.2018	0,82%	0,52%	-1,99%	0,06%	-2,55%	-2,73%	7,55%	5,96%
01.08.2018	0,82%	0,52%	-1,50%	0,35%	1,59%	5,70%	2,29%	6,92%
01.09.2018	0,82%	0,52%	1,48%	3,52%	5,89%	0,27%	-2,69%	-24,60%
01.10.2018	0,82%	0,52%	-2,72%	1,28%	1,20%	3,90%	7,42%	7,58%
01.11.2018	0,82%	0,52%	1,48%	1,53%	0,67%	1,18%	11,49%	4,40%
01.12.2018	0,82%	0,52%	1,48%	0,89%	5,89%	8,39%	11,49%	-13,56%
01.01.2019	0,82%	0,52%	1,48%	3,52%	1,93%	8,39%	11,49%	14,63%
01.02.2019	0,82%	0,52%	1,48%	3,52%	5,89%	8,39%	11,49%	14,63%

Table 6.3: the matrix X for the worst-case scenario

IR	*3,99%*	*4,99%*	*5,99%*	*8,49%*	*10,99%*	*13,49%*	*15,49%*	*19,99%*
3,99 %	0,94 %	0,11 %	0,07 %	0,42 %	0,72 %	1,22 %	0,97 %	0,66 %
4,99 %	0,11 %	0,19 %	0,06 %	0,21 %	0,48 %	0,56 %	0,84 %	0,61 %
5,99 %	0,07 %	0,06 %	0,54 %	0,43 %	0,67 %	0,95 %	1,08 %	-0,48 %
8,49 %	0,42 %	0,21 %	0,43 %	2,18 %	1,82 %	2,48 %	3,56 %	1,70 %
10,99 %	0,72 %	0,48 %	0,67 %	1,82 %	4,05 %	5,93 %	4,44 %	1,00 %
13,49 %	1,22 %	0,56 %	0,95 %	2,48 %	5,93 %	14,12 %	6,52 %	6,24 %
15,49 %	0,97 %	0,84 %	1,08 %	3,56 %	4,44 %	6,52 %	16,10 %	6,15 %
19,99 %	0,66 %	0,61 %	-0,48 %	1,70 %	1,00 %	6,24 %	6,15 %	26,68 %

And finally, the VCM where the variances of the monthly ROI lie on the diagonal

Table 6.4: the VCM for the worst-case scenario

IR	*3,99%*	*4,99%*	*5,99%*	*8,49%*	*10,99%*	*13,49%*	*15,49%*	*19,99%*
3,99 %	**0,028%**	0,003%	0,002%	0,012%	0,021%	0,036%	0,028%	0,019%
4,99 %	0,003%	**0,006%**	0,002%	0,006%	0,014%	0,017%	0,025%	0,018%
5,99 %	0,002%	0,002%	**0,016%**	0,013%	0,020%	0,028%	0,032%	-0,014%
8,49 %	0,012%	0,006%	0,013%	**0,064%**	0,054%	0,073%	0,105%	0,050%
10,99 %	0,021%	0,014%	0,020%	0,054%	**0,119%**	0,174%	0,131%	0,029%
13,49 %	0,036%	0,017%	0,028%	0,073%	0,174%	**0,415%**	0,192%	0,184%
15,49 %	0,028%	0,025%	0,032%	0,105%	0,131%	0,192%	**0,474%**	0,181%
19,99 %	0,019%	0,018%	-0,014%	0,050%	0,029%	0,184%	0,181%	**0,785%**

The obtained results from the Table 6.1 and VCM can be summarized in Table 6.5.

Table 6.5: summary of the worst-case

IR	*VAR*	*EXP*	*SD*	*SR*
3,99 %	0,03%	2,40 %	1,66 %	0,74
4,99 %	0,01%	3,30 %	0,75 %	2,82
5,99 %	0,02%	2,76 %	1,26 %	1,25
8,49 %	0,06%	1,83 %	2,53 %	0,26
10,99 %	0,12%	0,91 %	3,45 %	-0,08
13,49 %	0,42%	0,10 %	6,44 %	-0,17
15,49 %	0,47%	-1,72 %	6,88 %	-0,42
19,99 %	0,78%	-1,88 %	8,86 %	-0,35

The expected return of more risky categories is negative which corresponds to the fact that most of the defaulted loans which are expected to be highly unprofitable under this scenario belong to these riskier categories.

6.1.2 The second scenario

The same procedure is used for the second case as well. The tables of monthly ROI, the X matrix and VCM can be found in the Appendix. The results are summarized in the following table.

Table 6.6: summary, second scenario

IR	*VAR*	*EXP*	*SD*	*SR*
3,99 %	0,02%	2,62 %	1,25 %	1,15
4,99 %	0,00%	3,42 %	0,58 %	3,89
5,99 %	0,01%	3,08 %	0,98 %	1,94
8,49 %	0,04%	2,62 %	1,94 %	0,74
10,99 %	0,07%	2,25 %	2,57 %	0,42
13,49 %	0,25%	1,91 %	5,04 %	0,14
15,49 %	0,30%	0,54 %	5,47 %	-0,12
19,99 %	0,54%	0,71 %	7,33 %	-0,06

Under this slightly more optimistic scenario the expected return of all categories is positive but still much lower for the riskier categories than what Zonky promises. The standard deviation is now lower for all categories.

6.1.3 The best-case scenario

Table 6.7: summary, the best-case scenario

IR	*VAR*	*EXP*	*SD*	*SR*
3,99 %	0,004%	2,917%	0,624%	2,78
4,99 %	0,001%	3,614%	0,296%	8,23
5,99 %	0,003%	3,612%	0,570%	4,26
8,49 %	0,012%	3,897%	1,080%	2,52
10,99 %	0,019%	4,320%	1,395%	2,25
13,49 %	0,072%	4,889%	2,680%	1,38
15,49 %	0,108%	4,409%	3,280%	0,98
19,99 %	0,213%	5,449%	4,614%	0,93

Under the best-case scenario the expected returns improve further. The highest interest rates show the highest improvement. The obtained expected returns are now close to the promised returns if we do not consider taxes. The standard deviation is now lower compared to the two previous cases. The ROI and X matrices as well as the VCM can be found in the appendix.

6.2 Optimization

After obtaining the results we can now go to the next step which is the optimization. We will do the optimization assuming the correlation between loans as well as consider them being uncorrelated.

First, the expected return and the associated risk represented by the standard deviation of an equally weighted portfolio can be calculated to see its performance. In case of 8 asset classes the weight of each asset class is 1/8. The expected return will be derived as the weighted average of the expected returns given by Equation 4.4.
In order to get the standard deviation of this portfolio, we will use Equation 4.7.

After calculating the expected return (after tax and investment fees) and the standard deviation of the equally weighted portfolio we can do the optimization. The Excel Add-In called Solver which is useful for solving general optimization problems will be used. We will do two kinds of optimization. The first task is to find the weights which minimize the standard deviation of the portfolio while the goal of the second type of optimization is to find the portfolio maximizing the SR, so-called tangency portfolio. This is the optimal risky portfolio if we consider the risk-free asset to be available for the investor.

6.2.1 The worst-case scenario

Under our the most pessimistic scenario the Sharpe ratio of the equally weighted portfolio is negative. This is because the expected return of this portfolio is smaller than the return of the risk-free asset. The situation changes for portfolio which minimizes the standard deviation. The expected return increases significantly while the standard deviation is smaller than the standard deviation of the least risky asset in our portfolio. To reach the smallest standard deviation we should invest only in the first three loan categories which is similar to the composition of the portfolio which maximizes the Sharpe ratio. If zero correlation between the loan categories is assumed we obtain slightly better results in terms of Sharpe ratio for the second and third portfolio. Also, the asset mix changes. We should invest small proportion of our asset in the riskier assets in order to minimize the SD.

Table 6.8: portfolio optimization, worst-case scenario, non-zero correlation

Portfolio optimization - assuming non-zero correlation

Interest rate	*equally weighted portfolio*	*min SD*	*max Sharpe ratio*	
3,99 %	12,5%	6,8%	0,0%	Weights
4,99 %	12,5%	72,6%	85,7%	
5,99 %	12,5%	20,6%	14,3%	
8,49 %	12,5%	0,0%	0,0%	
10,99 %	12,5%	0,0%	0,0%	
13,49 %	12,5%	0,0%	0,0%	
15,49 %	12,5%	0,0%	0,0%	
19,99 %	12,5%	0,0%	0,0%	
sum of weights	100,0%	100,0%	100,0%	
expected return	**0,9616%**	**3,1274%**	**3,2227%**	
Standard deviation	**2,7422%**	**0,6844%**	**0,7000%**	
Sharpe ratio	**-0,0796**	**2,8456**	**2,9181**	

Table 6.9: portfolio optimization, worst-case scenario, zero correlation

Portfolio optimization - assuming zero correlation

Interest rate	*equally weighted portfolio*	*min SD*	*max Sharpe ratio*	
3,99 %	12,5%	11,9%	8,4%	Weights
4,99 %	12,5%	57,8%	70,9%	
5,99 %	12,5%	20,6%	18,8%	
8,49 %	12,5%	5,1%	1,9%	
10,99 %	12,5%	2,7%	0,0%	
13,49 %	12,5%	0,8%	0,0%	
15,49 %	12,5%	0,7%	0,0%	
19,99 %	12,5%	0,4%	0,0%	
sum of weights	100,0%	100,0%	100,0%	
expected return	**0,9616%**	**2,8602%**	**3,0949%**	
Standard deviation	**1,7256%**	**0,5710%**	**0,6009%**	
Sharpe ratio	**-0,1266**	**2,9426**	**3,1865**	

6.2.2 The second scenario

In this scenario all standard deviations and expected returns improve because we are more optimistic about the performance of defaulted loans. However, there still should not be any funds invested in the riskier loan categories when assuming non-zero correlation between the interest rate categories. The SR is significantly higher for the case of zero correlation.

Table 6.1.1: portfolio optimization, second scenario, non-zero correlation

Portfolio optimization - assuming non-zero correlation

Interest rate	*equally weighted portfolio*	*min SD*	*max Sharpe ratio*	
3,99 %	12,5%	7,9%	1,4%	Weights
4,99 %	12,5%	71,3%	80,9%	
5,99 %	12,5%	20,8%	17,7%	
8,49 %	12,5%	0,0%	0,0%	
10,99 %	12,5%	0,0%	0,0%	
13,49 %	12,5%	0,0%	0,0%	
15,49 %	12,5%	0,0%	0,0%	
19,99 %	12,5%	0,0%	0,0%	
sum of weights	100,0%	100,0%	100,0%	
expected return	**2,1452%**	**3,2890%**	**3,3514%**	
Standard deviation	**2,0556%**	**0,5200%**	**0,5277%**	
Sharpe ratio	**0,4695**	**4,0557**	**4,1152**	

Table 6.1.2: portfolio optimization, second scenario. Zero correlation

Portfolio optimization - assuming zero correlation

Interest rate	*equally weighted portfolio*	*min SD*	*max Sharpe ratio*	
3,99 %	12,5%	12,3%	9,0%	Weights
4,99 %	12,5%	57,9%	66,0%	
5,99 %	12,5%	20,0%	19,4%	
8,49 %	12,5%	5,1%	3,7%	
10,99 %	12,5%	2,9%	1,6%	
13,49 %	12,5%	0,8%	0,3%	
15,49 %	12,5%	0,6%	0,0%	
19,99 %	12,5%	0,4%	0,0%	
sum of weights	100,0%	100,0%	100,0%	
expected return	**2,1452%**	**3,1414%**	**3,2320%**	
Standard deviation	**1,3828%**	**0,4389%**	**0,4483%**	
Sharpe ratio	**0,6980**	**4,4688**	**4,5777**	

6.2.3 The best-case scenario

Not surprisingly, under the most optimistic scenario we get the best results. Compared to the previous portfolios we obtained, all portfolios in this case have higher expected return, lower risk and higher Sharpe ratio.

Table 6.1.3: portfolio optimization, best-case scenario, non-zero correlation

Portfolio optimization - assuming non-zero correlation

Interest rate	*equally weighted portfolio*	*min SD*	*max Sharpe ratio*	
3,99 %	12,5%	9,5%	4,0%	Weights
4,99 %	12,5%	71,8%	76,0%	
5,99 %	12,5%	18,4%	19,2%	
8,49 %	12,5%	0,0%	0,2%	
10,99 %	12,5%	0,0%	0,0%	
13,49 %	12,5%	0,0%	0,0%	
15,49 %	12,5%	0,0%	0,0%	
19,99 %	12,5%	0,3%	0,6%	
sum of weights	100,0%	100,0%	100,0%	
expected return	**4,1383%**	**3,5529%**	**3,5966%**	
Standard deviation	**1,0781%**	**0,2650%**	**0,2674%**	
Sharpe ratio	**2,7439**	**8,9553**	**9,0358**	

Table 6.1.4: portfolio optimization, best-case scenario, zero correlation

Portfolio optimization - assuming zero correlation

Interest rate	*equally weighted portfolio*	*min SD*	*max Sharpe ratio*	
3,99 %	12,5%	13,7%	10,0%	Weights
4,99 %	12,5%	61,1%	62,2%	
5,99 %	12,5%	16,4%	16,7%	
8,49 %	12,5%	4,6%	5,2%	
10,99 %	12,5%	2,7%	3,6%	
13,49 %	12,5%	0,7%	1,2%	
15,49 %	12,5%	0,5%	0,7%	
19,99 %	12,5%	0,3%	0,4%	
sum of weights	100,0%	100,0%	100,0%	
*expected return**	**4,1383%**	**3,5686%**	**3,6128%**	
Standard deviation	**0,8210%**	**0,2311%**	**0,2333%**	
Sharpe ratio	**3,6032**	**10,3346**	**10,4298**	

Conclusion

In this thesis we proposed a possible way of finding the optimal portfolio at Zonky platform using the MPT and the so-called rating-based approach. Due to lack of data we worked with three different scenarios, each with different assumption regarding the performance of defaulted loans. In the first case we assumed that no more payments will be paid. This case is rather unlikely, yet possible. The second scenario is slightly more optimistic using the data from the Prosper, one of the leading P2P companies in the US. The third scenario, the most optimistic one, is based on data from Bondora with relatively high rate of success in recovery operations. Based on the assumption used we obtained quite different results in terms of expected return and standard deviation of individual risk categories. Under the first scenario the expected return of the two riskiest categories turned out to be even negative. Therefore, we can conclude that high recovery rate is crucial for an investor to achieve high expected returns and should be closely examined by investors. Especially, if the investor decides to invest in riskier loans which were affected the most in our analysis. Under the first two scenarios we discovered that the charged interest rate was not enough to cover the risk the investor was bearing. The expected returns for the riskier categories were lower than for the categories with lower interest rate which are less risky. This is in line with the findings of Stiglitz and Weiss (1981) who believe that higher interest rate could imply a lower rate of return because higher interest rate attracts lower quality borrowers. Under the third scenario there was a positive correlation between the interest rate and the expected rate of return. However even in this case the less risky categories tend to have better trade-off between the risk and the expected return. Hence, for all three scenarios we obtained similar results to Singh, Gopal, & Li (2008). Assuming zero correlation between loan categories as Singh et al. (2008) or Guo et al. (2015) we, generally, obtained portfolios with higher Sharpe ratio (in some cases more than 10% higher) compared to the case when we assumed non-zero correlation between them. This contradicts the conclusion of Gue et al (2015) who considers the correlation between loans to be negligible and it is in line with the findings of Polák (2017). Besides that, we should invest in all risk categories to reach the lowest SD if we assume zero correlation between loans which is not the case of non-zero correlation. Nevertheless, the composition of the portfolio was similar to the case when we assumed non-zero correlation. We also found that the loan categories corresponding to lower interest rate offer better relationship between risk and return.

Generally speaking, we showed the usefulness of the MPT in its classical form for analyzing loans even though it is not its primal purpose.

Regardless of the scenario considered, we showed that diversification is beneficial for an investor. Thanks to diversification we were able to reach lower standard deviation than what was the lowest standard deviation among all assets building our portfolio in the respective scenario. The second type of optimization focused on maximizing the SR. We showed that portfolios resulting from both kinds of optimization performed better the equally portfolio in terms of the SR. Also, we found that irrespective of the optimization goal the composition of both kinds of portfolio was similar under each scenario. Even though the results show that diversification can result in relatively low level of risk (standard deviation was lower than 1% for all cases), investor should keep in mind that our results might not be a reliable investment guide. Firstly, investor should bear in mind that portfolio performance might be quite different in future from what the results in the past showed and the performance might worsen quickly under unfavorable economic conditions which Zonky still has not experienced. Secondly, we faced the deficiency of the historical observations which is a common problem when analyzing P2P loans as Chi, Ding and Peng (2019) points out. Thirdly, the assumptions we based our analysis on could be subject to bias. Especially, the actual recovery rate might differ from those of the P2P platforms operating abroad. Therefore, in order to achieve more accurate results, the analysis should be done when the data about the success rate of recovery operations of Zonky are available. Lastly, some approaches which do not consider each loan from the same risk category to have the same expected return and risk such as the instance based approach used by Guo (2015) showed better predicting accuracy.

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LIST OF TABLES AND FIGURES

Table A.1: number of PAID/PAID OFF loans in given month for given interest rate

	Interest rate							
month credited	*3,99%*	*4,99%*	*5,99%*	*8,49%*	*10,99%*	*13,49%*	*15,49%*	*19,99%*
01.03.2016	3	15	44	42	52	22	23	10
01.04.2016	1	19	44	29	21	30	15	9
01.05.2016	2	21	59	32	25	33	22	22
01.06.2016	6	14	42	28	23	21	24	13
01.07.2016	4	18	29	19	28	15	14	17
01.08.2016	4	16	37	22	25	23	14	15
01.09.2016	5	14	32	32	30	18	11	6
01.10.2016	4	18	31	26	23	25	18	19
01.11.2016	5	19	53	45	34	30	30	23
01.12.2016	2	24	50	41	31	47	44	19
01.01.2017	2	23	41	38	42	27	31	21
01.02.2017	2	29	54	32	33	22	15	16
01.03.2017	6	27	52	25	26	31	29	21
01.04.2017	10	29	42	36	35	19	15	15
01.05.2017	18	33	88	74	49	45	32	10
01.06.2017	19	46	115	76	79	51	30	22
01.07.2017	20	32	104	83	71	47	23	18
01.08.2017	20	54	115	87	67	55	34	18
01.09.2017	18	47	124	83	80	55	46	26
01.10.2017	19	63	118	110	97	60	55	18
01.11.2017	37	68	130	107	117	78	59	28
01.12.2017	24	38	107	87	73	56	41	27
01.01.2018	11	52	115	82	82	53	36	24
01.02.2018	21	55	97	89	70	58	41	19
01.03.2018	13	42	98	109	92	72	40	34
01.04.2018	24	33	91	90	86	70	45	31
01.05.2018	30	49	100	88	79	60	39	18
01.06.2018	30	53	97	73	74	44	34	19
01.07.2018	16	40	86	56	47	38	26	24
01.08.2018	15	34	68	58	48	40	34	27
01.09.2018	15	32	49	50	40	26	23	20
01.10.2018	9	33	74	47	68	24	27	16
01.11.2018	5	29	50	53	61	30	19	22
01.12.2018	5	17	34	40	36	14	14	4
01.01.2019	3	11	19	31	27	13	9	6
01.02.2019	1	4	8	21	14	10	5	6
sum	**429**	**1151**	**2497**	**2041**	**1885**	**1362**	**1017**	**663**

Table A.2: average ROI – second scenario

	Interest rate							
month credited	*3,99%*	*4,99%*	*5,99%*	*8,49%*	*10,99%*	*13,49%*	*15,49%*	*19,99%*
01.03.2016	*3,2%*	*3,8%*	*4,2%*	*4,8%*	*5,6%*	*6,9%*	*4,0%*	*5,9%*
01.04.2016	*3,2%*	*3,8%*	*2,7%*	*5,3%*	*6,3%*	*6,6%*	*-3,3%*	*-2,7%*
01.05.2016	*3,2%*	*3,8%*	*3,3%*	*5,3%*	*5,4%*	*7,6%*	*7,9%*	*5,8%*
01.06.2016	*3,2%*	*3,8%*	*4,2%*	*4,5%*	*5,7%*	*8,5%*	*8,7%*	*8,0%*
01.07.2016	*3,2%*	*3,8%*	*4,2%*	*1,7%*	*4,7%*	*4,7%*	*6,4%*	*-0,1%*
01.08.2016	*3,2%*	*3,8%*	*2,5%*	*5,3%*	*4,0%*	*5,0%*	*2,0%*	*8,4%*
01.09.2016	*3,2%*	*3,8%*	*4,2%*	*4,4%*	*4,8%*	*8,5%*	*5,7%*	*-7,5%*
01.10.2016	*3,2%*	*3,8%*	*4,2%*	*4,4%*	*1,7%*	*5,3%*	*5,3%*	*8,3%*
01.11.2016	*3,2%*	*3,8%*	*3,5%*	*4,4%*	*4,5%*	*7,8%*	*0,4%*	*-0,1%*
01.12.2016	*3,2%*	*3,8%*	*4,2%*	*4,1%*	*2,6%*	*2,8%*	*1,5%*	*-5,3%*
01.01.2017	*3,2%*	*3,8%*	*3,0%*	*5,3%*	*5,4%*	*5,7%*	*-1,5%*	*9,2%*
01.02.2017	*3,2%*	*3,8%*	*4,2%*	*5,3%*	*5,3%*	*5,5%*	*4,0%*	*3,7%*
01.03.2017	*3,2%*	*3,8%*	*3,0%*	*1,5%*	*5,1%*	*7,6%*	*3,8%*	*-0,4%*
01.04.2017	*3,2%*	*3,8%*	*2,9%*	*3,8%*	*-1,2%*	*-14,6%*	*7,7%*	*-2,1%*
01.05.2017	*3,2%*	*3,8%*	*1,3%*	*-0,2%*	*3,1%*	*3,2%*	*-1,1%*	*-2,8%*
01.06.2017	*3,2%*	*3,8%*	*2,7%*	*2,7%*	*2,1%*	*-3,4%*	*-5,6%*	*-4,8%*
01.07.2017	*1,6%*	*3,8%*	*2,3%*	*1,7%*	*0,5%*	*-2,6%*	*-3,6%*	*8,1%*
01.08.2017	*3,2%*	*2,1%*	*2,2%*	*1,7%*	*-0,7%*	*2,7%*	*-9,9%*	*7,2%*
01.09.2017	*3,2%*	*3,0%*	*2,9%*	*0,8%*	*1,1%*	*3,9%*	*-1,0%*	*-2,8%*
01.10.2017	*3,2%*	*2,1%*	*4,2%*	*1,4%*	*0,8%*	*-0,4%*	*-1,5%*	*-8,9%*
01.11.2017	*0,7%*	*3,8%*	*3,8%*	*0,9%*	*3,9%*	*1,2%*	*-1,2%*	*-4,9%*
01.12.2017	*0,6%*	*3,8%*	*3,0%*	*0,9%*	*0,7%*	*-2,6%*	*-0,6%*	*1,2%*
01.01.2018	*-3,1%*	*2,6%*	*3,3%*	*2,9%*	*-1,0%*	*-2,0%*	*-0,7%*	*-3,1%*
01.02.2018	*3,2%*	*2,7%*	*2,7%*	*3,7%*	*1,3%*	*-0,5%*	*2,0%*	*-9,4%*
01.03.2018	*3,2%*	*3,8%*	*3,4%*	*-1,9%*	*0,4%*	*-0,8%*	*-6,6%*	*3,4%*
01.04.2018	*3,2%*	*3,8%*	*3,5%*	*2,9%*	*0,7%*	*2,2%*	*-5,7%*	*-1,9%*
01.05.2018	*3,2%*	*2,1%*	*2,8%*	*3,1%*	*0,6%*	*-2,6%*	*-2,3%*	*-0,4%*
01.06.2018	*3,2%*	*3,8%*	*3,5%*	*3,2%*	*0,0%*	*-0,2%*	*1,5%*	*0,6%*
01.07.2018	*3,2%*	*3,8%*	*1,7%*	*2,6%*	*0,6%*	*-0,3%*	*6,8%*	*6,4%*
01.08.2018	*3,2%*	*3,8%*	*1,9%*	*3,2%*	*3,6%*	*6,4%*	*3,3%*	*6,7%*
01.09.2018	*3,2%*	*3,8%*	*4,2%*	*5,3%*	*6,8%*	*2,3%*	*-1,6%*	*-19,6%*
01.10.2018	*3,2%*	*3,8%*	*0,9%*	*3,5%*	*3,0%*	*4,9%*	*6,3%*	*6,6%*
01.11.2018	*3,2%*	*3,8%*	*4,2%*	*3,7%*	*2,6%*	*2,6%*	*9,8%*	*4,4%*
01.12.2018	*3,2%*	*3,8%*	*4,2%*	*3,1%*	*6,8%*	*8,5%*	*9,8%*	*-12,4%*
01.01.2019	*3,2%*	*3,8%*	*4,2%*	*5,3%*	*3,5%*	*8,5%*	*9,8%*	*12,7%*
01.02.2019	*3,2%*	*3,8%*	*4,2%*	*5,3%*	*6,8%*	*8,5%*	*9,8%*	*12,7%*
weighted average	***2,6%***	***3,4%***	***3,1%***	***2,6%***	***2,3%***	***1,9%***	***0,5%***	***0,7%***

Table A.3: excess return matrix, second scenario

	Interest rate							
month credited	*3,99%*	*4,99%*	*5,99%*	*8,49%*	*10,99%*	*13,49%*	*15,49%*	*19,99%*
01.03.2016	0,6%	0,4%	1,2%	2,2%	3,3%	5,0%	3,5%	5,2%
01.04.2016	0,6%	0,4%	-0,4%	2,7%	4,0%	4,7%	-3,8%	-3,4%
01.05.2016	0,6%	0,4%	0,2%	2,7%	3,1%	5,7%	7,3%	5,1%
01.06.2016	0,6%	0,4%	1,2%	1,9%	3,5%	6,6%	8,1%	7,3%
01.07.2016	0,6%	0,4%	1,2%	-1,0%	2,5%	2,8%	5,8%	-0,8%
01.08.2016	0,6%	0,4%	-0,6%	2,7%	1,8%	3,1%	1,4%	7,7%
01.09.2016	0,6%	0,4%	1,2%	1,7%	2,5%	6,6%	5,1%	-8,2%
01.10.2016	0,6%	0,4%	1,2%	1,8%	-0,6%	3,4%	4,7%	7,6%
01.11.2016	0,6%	0,4%	0,4%	1,8%	2,3%	5,9%	-0,2%	-0,8%
01.12.2016	0,6%	0,4%	1,2%	1,5%	0,4%	0,9%	1,0%	-6,0%
01.01.2017	0,6%	0,4%	-0,1%	2,7%	3,1%	3,8%	-2,0%	8,5%
01.02.2017	0,6%	0,4%	1,2%	2,7%	3,1%	3,6%	3,5%	2,9%
01.03.2017	0,6%	0,4%	-0,1%	-1,1%	2,9%	5,7%	3,2%	-1,1%
01.04.2017	0,6%	0,4%	-0,2%	1,1%	-3,4%	-16,6%	7,1%	-2,8%
01.05.2017	0,6%	0,4%	-1,8%	-2,8%	0,8%	1,3%	-1,6%	-3,5%
01.06.2017	0,6%	0,4%	-0,4%	0,1%	-0,1%	-5,3%	-6,2%	-5,5%
01.07.2017	-1,0%	0,4%	-0,8%	-0,9%	-1,8%	-4,5%	-4,1%	7,4%
01.08.2017	0,6%	-1,3%	-0,8%	-0,9%	-3,0%	0,8%	-10,5%	6,5%
01.09.2017	0,6%	-0,4%	-0,2%	-1,8%	-1,2%	2,0%	-1,5%	-3,5%
01.10.2017	0,6%	-1,3%	1,2%	-1,2%	-1,5%	-2,3%	-2,0%	-9,6%
01.11.2017	-1,9%	0,4%	0,7%	-1,7%	1,7%	-0,7%	-1,7%	-5,6%
01.12.2017	-2,1%	0,4%	-0,1%	-1,7%	-1,6%	-4,5%	-1,2%	0,5%
01.01.2018	-5,7%	-0,9%	0,2%	0,3%	-3,3%	-3,9%	-1,3%	-3,8%
01.02.2018	0,6%	-0,7%	-0,4%	1,1%	-0,9%	-2,4%	1,5%	-10,1%
01.03.2018	0,6%	0,4%	0,3%	-4,6%	-1,8%	-2,7%	-7,2%	2,7%
01.04.2018	0,6%	0,4%	0,4%	0,3%	-1,5%	0,3%	-6,3%	-2,6%
01.05.2018	0,6%	-1,3%	-0,3%	0,5%	-1,6%	-4,5%	-2,9%	-1,1%
01.06.2018	0,6%	0,3%	0,4%	0,6%	-2,3%	-2,2%	1,0%	-0,1%
01.07.2018	0,6%	0,4%	-1,4%	0,0%	-1,6%	-2,2%	6,3%	5,7%
01.08.2018	0,6%	0,4%	-1,2%	0,6%	1,4%	4,5%	2,8%	6,0%
01.09.2018	0,6%	0,4%	1,2%	2,7%	4,5%	0,4%	-2,1%	-20,3%
01.10.2018	0,6%	0,4%	-2,2%	0,8%	0,8%	3,0%	5,7%	5,8%
01.11.2018	0,6%	0,4%	1,2%	1,1%	0,3%	0,6%	9,2%	3,7%
01.12.2018	0,6%	0,4%	1,2%	0,4%	4,5%	6,6%	9,2%	-13,2%
01.01.2019	0,6%	0,4%	1,2%	2,7%	1,2%	6,6%	9,2%	12,0%
01.02.2019	0,6%	0,4%	1,2%	2,7%	4,5%	6,6%	9,2%	12,0%

Table A.4: X matrix, second scenario

IR	*3,99%*	*4,99%*	*5,99%*	*8,49%*	*10,99%*	*13,49%*	*15,49%*	*19,99%*
3,99 %	0,532%	0,063%	0,027%	0,214%	0,393%	0,689%	0,524%	0,274%
4,99 %	0,063%	0,113%	0,030%	0,113%	0,270%	0,316%	0,476%	0,275%
5,99 %	0,027%	0,030%	0,327%	0,221%	0,329%	0,496%	0,620%	-0,426%
8,49 %	0,214%	0,113%	0,221%	1,284%	0,951%	1,405%	1,816%	0,846%
10,99 %	0,393%	0,270%	0,329%	0,951%	2,252%	3,416%	2,206%	-0,119%
13,49 %	0,689%	0,316%	0,496%	1,405%	3,416%	8,641%	3,529%	3,015%
15,49 %	0,524%	0,476%	0,620%	1,816%	2,206%	3,529%	10,172%	3,201%
19,99 %	0,274%	0,275%	-0,426%	0,846%	-0,119%	3,015%	3,201%	18,290%

Table A.5: VCM, the second scenario

IR	*3,99%*	*4,99%*	*5,99%*	*8,49%*	*10,99%*	*13,49%*	*15,49%*	*19,99%*
3,99 %	**0,016%**	0,002%	0,001%	0,006%	0,012%	0,020%	0,015%	0,008%
4,99 %	0,002%	**0,003%**	0,001%	0,003%	0,008%	0,009%	0,014%	0,008%
5,99 %	0,001%	0,001%	**0,010%**	0,006%	0,010%	0,015%	0,018%	-0,013%
8,49 %	0,006%	0,003%	0,006%	**0,038%**	0,028%	0,041%	0,053%	0,025%
10,99 %	0,012%	0,008%	0,010%	0,028%	**0,066%**	0,100%	0,065%	-0,003%
13,49 %	0,020%	0,009%	0,015%	0,041%	0,100%	**0,254%**	0,104%	0,089%
15,49 %	0,015%	0,014%	0,018%	0,053%	0,065%	0,104%	**0,299%**	0,094%
19,99 %	0,008%	0,008%	-0,013%	0,025%	-0,003%	0,089%	0,094%	**0,538%**

Table A.6: average ROI – best-case scenario

	Interest rate							
month credited	*3,99%*	*4,99%*	*5,99%*	*8,49%*	*10,99%*	*13,49%*	*15,49%*	*19,99%*
01.03.2016	3,2%	3,8%	4,2%	5,0%	5,6%	6,9%	5,3%	7,5%
01.04.2016	3,2%	3,8%	2,8%	5,3%	6,4%	7,4%	-2,1%	-2,7%
01.05.2016	3,2%	3,8%	3,3%	5,3%	5,9%	8,0%	8,4%	5,9%
01.06.2016	3,2%	3,8%	4,2%	4,8%	6,2%	8,5%	9,1%	9,9%
01.07.2016	3,2%	3,8%	4,2%	1,7%	5,7%	4,7%	8,0%	3,2%
01.08.2016	3,2%	3,8%	2,5%	5,3%	5,3%	6,6%	3,3%	9,6%
01.09.2016	3,2%	3,8%	4,2%	4,7%	5,4%	8,5%	7,5%	-4,1%
01.10.2016	3,2%	3,8%	4,2%	4,8%	1,7%	6,7%	7,0%	10,0%
01.11.2016	3,2%	3,8%	3,8%	4,9%	5,6%	8,0%	3,7%	4,4%
01.12.2016	3,2%	3,8%	4,2%	4,7%	4,4%	5,4%	3,2%	0,2%
01.01.2017	3,2%	3,8%	3,6%	5,3%	6,0%	6,9%	1,9%	10,4%
01.02.2017	3,2%	3,8%	4,2%	5,3%	5,9%	6,8%	6,6%	7,5%
01.03.2017	3,2%	3,8%	3,6%	3,3%	5,7%	8,0%	6,6%	5,1%
01.04.2017	3,2%	3,8%	3,6%	4,5%	2,7%	-3,9%	8,6%	4,2%

01.05.2017	3,2%	3,8%	2,7%	2,4%	4,9%	5,7%	3,8%	3,4%
01.06.2017	3,2%	3,8%	3,5%	3,9%	4,3%	1,6%	1,0%	2,3%
01.07.2017	2,4%	3,8%	3,2%	3,4%	3,5%	2,6%	1,8%	10,0%
01.08.2017	3,2%	2,9%	3,2%	3,5%	2,9%	5,3%	-0,9%	9,1%
01.09.2017	3,2%	3,4%	3,6%	3,0%	3,7%	6,0%	3,8%	3,9%
01.10.2017	3,2%	3,0%	4,2%	3,3%	3,6%	3,7%	3,6%	0,8%
01.11.2017	1,9%	3,8%	4,0%	3,1%	5,3%	4,6%	3,9%	3,0%
01.12.2017	1,9%	3,8%	3,6%	3,0%	3,6%	2,5%	4,1%	6,1%
01.01.2018	0,1%	3,2%	3,8%	4,1%	2,6%	3,0%	3,8%	3,8%
01.02.2018	3,2%	3,2%	3,5%	4,5%	3,9%	3,7%	5,5%	0,5%
01.03.2018	3,2%	3,8%	3,8%	1,6%	3,4%	3,6%	1,0%	7,4%
01.04.2018	3,2%	3,8%	3,9%	4,0%	3,6%	4,9%	1,5%	4,4%
01.05.2018	3,2%	2,9%	3,5%	4,2%	3,6%	2,5%	3,3%	5,4%
01.06.2018	3,2%	3,8%	3,9%	4,2%	3,1%	3,9%	5,3%	6,0%
01.07.2018	3,2%	3,8%	2,9%	3,9%	3,5%	3,8%	8,2%	9,2%
01.08.2018	3,2%	3,8%	3,0%	4,2%	5,1%	7,4%	6,6%	9,3%
01.09.2018	3,2%	3,8%	4,2%	5,3%	6,8%	5,0%	3,5%	-5,4%
01.10.2018	3,2%	3,8%	2,4%	4,3%	4,7%	6,5%	7,8%	9,2%
01.11.2018	3,2%	3,8%	4,2%	4,4%	4,4%	5,1%	9,8%	8,0%
01.12.2018	3,2%	3,8%	4,2%	4,1%	6,8%	8,5%	9,8%	-2,0%
01.01.2019	3,2%	3,8%	4,2%	5,3%	4,9%	8,5%	9,8%	12,7%
01.02.2019	3,2%	3,8%	4,2%	5,3%	6,8%	8,5%	9,8%	12,7%
weighted average	**2,9%**	**3,6%**	**3,6%**	**3,9%**	**4,3%**	**4,9%**	**4,4%**	**5,4%**

Table A.7: excess return matrix, best-case scenario

	Interest rate							
month credited	*3,99%*	*4,99%*	*5,99%*	*8,49%*	*10,99%*	*13,49%*	*15,49%*	*19,99%*
01.03.2016	0,3%	0,2%	0,6%	1,2%	1,3%	2,0%	0,9%	2,1%
01.04.2016	0,3%	0,2%	-0,8%	1,4%	2,1%	2,5%	-6,6%	-8,2%
01.05.2016	0,3%	0,2%	-0,4%	1,4%	1,6%	3,1%	4,0%	0,5%
01.06.2016	0,3%	0,2%	0,6%	0,9%	1,9%	3,6%	4,7%	4,4%
01.07.2016	0,3%	0,2%	0,6%	-2,2%	1,3%	-0,2%	3,6%	-2,2%
01.08.2016	0,3%	0,2%	-1,1%	1,4%	1,0%	1,7%	-1,1%	4,1%
01.09.2016	0,3%	0,2%	0,6%	0,8%	1,0%	3,6%	3,1%	-9,5%
01.10.2016	0,3%	0,2%	0,6%	0,9%	-2,6%	1,8%	2,6%	4,6%
01.11.2016	0,3%	0,2%	0,2%	1,0%	1,2%	3,2%	-0,7%	-1,0%
01.12.2016	0,3%	0,2%	0,6%	0,8%	0,1%	0,5%	-1,2%	-5,2%
01.01.2017	0,3%	0,2%	0,0%	1,4%	1,7%	2,0%	-2,5%	4,9%
01.02.2017	0,3%	0,2%	0,6%	1,4%	1,6%	1,9%	2,2%	2,1%

01.03.2017	0,3%	0,2%	0,0%	-0,6%	1,4%	3,1%	2,2%	-0,3%
01.04.2017	0,3%	0,2%	0,0%	0,6%	-1,6%	-8,8%	4,1%	-1,3%
01.05.2017	0,3%	0,2%	-0,9%	-1,5%	0,6%	0,8%	-0,6%	-2,0%
01.06.2017	0,3%	0,2%	-0,1%	0,0%	0,0%	-3,3%	-3,4%	-3,2%
01.07.2017	-0,5%	0,2%	-0,4%	-0,5%	-0,9%	-2,3%	-2,6%	4,6%
01.08.2017	0,3%	-0,7%	-0,4%	-0,4%	-1,4%	0,4%	-5,3%	3,6%
01.09.2017	0,3%	-0,2%	-0,1%	-0,9%	-0,6%	1,1%	-0,7%	-1,5%
01.10.2017	0,3%	-0,6%	0,6%	-0,6%	-0,7%	-1,2%	-0,9%	-4,7%
01.11.2017	-1,0%	0,2%	0,4%	-0,8%	1,0%	-0,3%	-0,5%	-2,5%
01.12.2017	-1,0%	0,2%	0,0%	-0,9%	-0,7%	-2,4%	-0,3%	0,6%
01.01.2018	-2,8%	-0,4%	0,1%	0,2%	-1,7%	-1,9%	-0,6%	-1,6%
01.02.2018	0,3%	-0,4%	-0,1%	0,6%	-0,4%	-1,2%	1,1%	-5,0%
01.03.2018	0,3%	0,2%	0,2%	-2,3%	-0,9%	-1,3%	-3,4%	2,0%
01.04.2018	0,3%	0,2%	0,3%	0,1%	-0,7%	0,1%	-2,9%	-1,1%
01.05.2018	0,3%	-0,7%	-0,1%	0,3%	-0,8%	-2,4%	-1,1%	0,0%
01.06.2018	0,3%	0,2%	0,2%	0,3%	-1,2%	-1,0%	0,9%	0,6%
01.07.2018	0,3%	0,2%	-0,7%	0,0%	-0,8%	-1,1%	3,7%	3,8%
01.08.2018	0,3%	0,2%	-0,6%	0,3%	0,8%	2,5%	2,2%	3,8%
01.09.2018	0,3%	0,2%	0,6%	1,4%	2,5%	0,2%	-0,9%	-10,8%
01.10.2018	0,3%	0,2%	-1,2%	0,4%	0,4%	1,6%	3,4%	3,8%
01.11.2018	0,3%	0,2%	0,6%	0,5%	0,1%	0,2%	5,4%	2,5%
01.12.2018	0,3%	0,2%	0,6%	0,2%	2,5%	3,6%	5,4%	-7,4%
01.01.2019	0,3%	0,2%	0,6%	1,4%	0,6%	3,6%	5,4%	7,3%
01.02.2019	0,3%	0,2%	0,6%	1,4%	2,5%	3,6%	5,4%	7,3%

Table A.8: X matrix, the best-case scenario

IR	*3,99%*	*4,99%*	*5,99%*	*8,49%*	*10,99%*	*13,49%*	*15,49%*	*19,99%*
3,99 %	0,133%	0,015%	0,002%	0,051%	0,095%	0,173%	0,127%	0,020%
4,99 %	0,015%	0,030%	0,005%	0,025%	0,066%	0,081%	0,117%	0,040%
5,99 %	0,002%	0,005%	0,111%	0,024%	0,043%	0,080%	0,217%	-0,153%
8,49 %	0,051%	0,025%	0,024%	0,397%	0,201%	0,384%	0,301%	0,117%
10,99 %	0,095%	0,066%	0,043%	0,201%	0,662%	0,837%	0,415%	-0,416%
13,49 %	0,173%	0,081%	0,080%	0,384%	0,837%	2,441%	0,817%	0,451%

15,49 %	0,127%	0,117%	0,217%	0,301%	0,415%	0,817%	3,657%	1,178%
19,99 %	0,020%	0,040%	-0,153%	0,117%	-0,416%	0,451%	1,178%	7,238%

Table A.9: VCM, the best-case scenario

IR	*3,99%*	*4,99%*	*5,99%*	*8,49%*	*10,99%*	*13,49%*	*15,49%*	*19,99%*
3,99 %	0,004%	0,000%	0,000%	0,001%	0,003%	0,005%	0,004%	0,001%
4,99 %	0,000%	0,001%	0,000%	0,001%	0,002%	0,002%	0,003%	0,001%
5,99 %	0,000%	0,000%	0,003%	0,001%	0,001%	0,002%	0,006%	-0,004%
8,49 %	0,001%	0,001%	0,001%	0,012%	0,006%	0,011%	0,009%	0,003%
10,99 %	0,003%	0,002%	0,001%	0,006%	0,019%	0,025%	0,012%	-0,012%
13,49 %	0,005%	0,002%	0,002%	0,011%	0,025%	0,072%	0,024%	0,013%
15,49 %	0,004%	0,003%	0,006%	0,009%	0,012%	0,024%	0,108%	0,035%
19,99 %	0,001%	0,001%	-0,004%	0,003%	-0,012%	0,013%	0,035%	0,213%