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Should you put some of your eggs in the peer-to-peer lending basket?

Portfolio optimization with an Estonian P2P portfolio and traditional financial assets

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Abstract

This thesis examines whether an Estonian peer-to-peer loan portfolio can be an attractive diversification opportunity for retail investors. The posed research question is answered using the data from the Estonian P2P lending platform Bondora from 1 January 2013 to 31 December 2017 and using two different approaches: The Modern Portfolio Theory and the Treynor-Black Model. The empirical research results showcase that the Estonian aggregated P2P portfolio should be added to an investment portfolio in order to achieve better risk-reward trade-off.

Keywords: Peer-to-Peer (P2P) lending, Modern Portfolio Theory, Treynor-Black model

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1 Introduction

The lending and borrowing procedures of the traditional banks have become more and more rigid over time, which has created a possibility for innovation in the field (Bajpai 2016). Thus, peer-to-peer (P2P) lending and marketplaces were born. P2P lending or marketplace lending means that people ("peers") lend funds directly to borrowers without going through traditional financial intermediaries, such as banks (Akkizidis & Stagars 2016). The main advantages of P2P platforms are simpler and quicker procedures, thus quicker decisions and better interest rates for both borrowers and lenders, furthermore, P2P lending offers greater transparency (Akkizidis & Stagars 2016; Bajpai 2016). P2P lending started in UK with Zopa 2005 and in the United States with Prosper 2006 (Akkizidis & Stagars 2016).

The revenue for the platforms comes from origination fees and service fees. The loans offered are short to medium-term with a maximum of 60 months' time period with fixed interest rates (Ibid).

1.1 Background

When looking through the lens of established financial markets and how banks are functioning, P2P platforms have some risky and different characteristics (Akkizidis & Stagars 2016).

First element of the P2P lending is that loans that you could invest in are relatively risky, so lenders need to have a relatively low risk aversion (Ibid). However, a reason for taking the risks could be that the risk could be diversified through the small exposure of individual loans, often as small as € 5, as shown on Bondora's platform (Akkizidis & Stagars 2016; Bondora u.a).

As Akkizidis and Stagars (2016) describe the second element of P2P lending is that P2P loans have a fixed rate and thus will almost never be re-priced. They add that, this would be appropriate if the market never changes, which is not the case for P2P loans. Research shows that fixed rates work precisely with short-term loans that for example last for two days and that roll over continuously under new terms (Akkizidis & Stagars 2016). This kind of rate system could make sense either in very liquid market or where there exist a lot of trust between borrowers and lenders, neither of these applies to the P2P loans (Ibid). Fixed rate is profitable when they exceed the floating rate, however volatile market may result in greater losses (Ibid). Fixed loans also make sense in frozen markets where rates have nowhere to go (Ibid). However, because markets are not effectively frozen, applying real-world economic scenarios to P2P loan portfolios makes sense (Akkizidis & Stagars 2016).

According to Akkizidis and Stagars (2016) the third element is that P2P loans are short to medium term. Potentially, there are high spreads between lending and borrowing rates, which implies high credit losses and a low credit rating for each counterparty (Akkizidis & Stagars 2016).

The fourth element of the P2P lending is information asymmetry between platforms, lenders and borrowers (Cai et al. 2016). The investors' success with the borrower is dependent on the platforms' credit assessment. Platforms do not share the valuation process information and often the loan data is not available publicly (Milne & Parboteeah 2016).

Risks with P2P lending

No investment is without risk, not even in the case of P2P lending. The first risk for investors is the loan default risk (Milne & Parboteeah 2016). The industry provides relatively high levels of information on historical loan defaults and projections of future performance, however the default rates in some cases are relatively high (Ibid; see Bouteille & Coogan 2013; Servigny & Renault 2004;). Many platforms are offering some compensation for the default but even if the portfolios are diversified, the variability of default and loss over the business cycle remains unprotected (Milne & Parboteeah 2016). Losses can be highly influenced by economic recessions and may easily exhaust a default fund that is offering protection up to an amount that would cover the average annual level of default (Ibid). Banks have already specialized units that work on minimizing the post-default loan risk, however it is unclear, how much work P2P lenders conduct in order to minimize these kinds of losses (Ibid). In P2P lending the risk of the credit assessment is partly transferred to lenders rather than financial institutions (Ibid). Many of the borrowers are sub-prime borrowers who are not able to get loans from the bank (Pokornáa & Sponera 2016).

The second high risk related to the platform is performance. Investors are not protected against platform failures such as bankruptcy or the possibility of operational failure (Milne & Parboteeah 2016). As P2P lending platforms often do not have banking license there is no requirement to contribute to a fund of deposit insurance which leaves the lenders' investments uninsured (Pokornáa & Sponera 2016). A good example of this risk is the Swedish platform TrustBuddy's bankruptcy, where the lenders lost large amounts of funds (Mölne 2017).

Finally, further risks related to P2P lending are dangers of fraud, cybercrime and operational outages (Pokornáa & Sponera 2016).

Benefits from P2P lending

There are several advantages for investors of using the P2P lending as an investment instrument. The main attractive element for investors is high returns that are offered by P2P firms (Pokornáa & Sponera 2016). Returns of 10 % or higher are offered by larger P2P platforms (Ibid). The period is relatively short for the investments compared to bond investments.

Another aspect which makes P2P lending attractive is that investors do not need to spend lots of time on investment decisions. On many platforms investors can choose either to invest manually or to use the platform's big data automatic investment tool (Bondora u.a; Pokornáa & Sponera 2016). The investment tool helps investors construct portfolios that maximize the risk-adjusted returns based on investors' investment objectives (Pokornáa & Sponera 2016).

In the beginning, P2P investment was highly illiquid, however today the investors can often participate on the secondary market where loan portfolios can be traded and through that investments can be liquidated (Akkizidis & Stagars 2016).

Finally, there may be diversification benefits of adding P2P to a passive portfolio, as there are a few studies (i.e. Morse 2015) that show that P2P investment could be useful for individual investors to hedge their portfolio against local economic conditions or other exposure in their portfolio and Deloitte (2018) have found that it covaries relatively little with other financial assets.

Bondora

Since we use platform data from Bondora, we will now provide a short description of the platform and its business model.

Bondora is the first Estonian-based P2P lending marketplace and is focused on consumer loans (Bondora u.a). Bondora has branched out and now gives loans also in Spain, Slovakia and Finland. The company was founded in the end of 2009 and almost 36 000 investors have already invested more than €125 million in loans and have received 18 million in interest (Bondora u.a). The platform is accessible to most investors based in Europe, Switzerland and Norway (Ibid). Like many other platforms in Europe, they have no fees for investors on the primary market

(Ibid). The only fees investors have to pay is when they invest on the secondary market where investors are buying shares in loans that other people already invested in (Ibid).

1.2. Problem discussion

P2P is a relatively new way of lending and borrowing funds, which also means that the most literature is concentrating on how and what are the special characteristics of P2P lending as such (Jang et al. 2018). Existing research has largely focused on identifying the economic factors that influence funding success, including interest rates of loan requests, transaction history, etc (Ryan et al. 2007; Berger & Gleisner 2009; Collier & Hampshire 2010). The main focus in current literature is borrower evaluation from psychological-behavioral perspective rather than the effectiveness of investing in P2P lending as its own asset class (Galloway 2009; Greiner et al. 2009; Herzenstein et al. 2010; Ravina 2008). There is some research focused on finding factors which impact the likelihood of the funding of the loan and interest rate setting and, if these factors have influence in default rate (Iyer et al. 2011; Ceyhan et al. 2011; Freedman & Jin 2011; Klafft 2008). There are few papers analyzing P2P lending attractiveness from investor point of view (Luo et al. 2011; Liao et al 20149. To our knowledge, only one paper, Marot et al. (2017), has looked at P2P as an asset class that is compared and combined with the market portfolio.

There are a few authors which have researched the investors' possibility to earn money on the platforms, however, these studies have concluded that on average, the investor operates at a loss (Ceyhan et al. 2011; Freedman & Jin 2011; Klafft 2008; Singh et al 2009). In other words, the research is mainly concentrated on the P2P platforms as such and not comparing it to the whole financial market. Studies are mainly looking at the platforms in use in the USA and China and not much insight into European platforms, such as the Estonian platform Bondora, is provided. As mentioned above, there is only one study available which analyses P2P lending as an asset class from financial markets' point of view.

1.3 Research question and approach

This paper aims to answer the following question: *Should the Estonian aggregate P2P portfolio be added to an investor's portfolio in order to achieve better risk-reward trade-off?*

To answer the research question, we use two different theoretical bases, which are Modern Portfolio Theory and the Treynor-Black model. For each approach, we have three scenarios that will be described more closely in the methodology section. We analyze the aggregate Bondora P2P lending portfolio as a separate asset class. The aggregate portfolio approach is used since most of the investors on the platforms are using auto-investing service, which means that investors do not need to actively choose which loans to invest in. The answer to the research question, for both theories, is that it is positive if the weight on the P2P asset class in the results is greater than zero.

1.4 Contribution

This study enriches the discussions about P2P lending by including it in a combined analysis that examines the diversification benefits that can be achieved by adding a potentially uncorrelated asset to a well-diversified portfolio. We explore whether it would be an attractive investment to add to a retail investors' portfolio. Further, we analyse what to the best of our knowledge is a market that has not previously been academically studied, namely the Estonian P2P market.

1.5 Delimitations

Although Bondora provides loans for borrowers in multiple countries, we have chosen to only focus on the Estonian P2P market in order to simplify the empirical strategy. The delimitation enables us to avoid issues with institutional differences between countries. We only analyze the repayments during the time horizon between January 1, 2013 and December 31, 2017. We also consider just two additional asset classes beyond the P2P asset class in our mean-variance optimization problem and in the construction of the active portfolio, similarly to Marot et al (2017). We only solve the portfolio optimization problem and the construction of the active portfolio for a retail investor, who does not have access to all the asset classes in the investment universe.

2 Theory and methodology

In this section, we shortly describe Modern Portfolio Theory and the Treynor-Black model, and lay out the framework for our methodology, which we use to investigate our research question. We use these theories since they allow us to answer our research question in a simple and objective way. The theories differ as to how they measure risk and return: Modern portfolio Theory looks at the total portfolio risk while the Treynor-Black model only looks at the extra risk that is incurred by adding a mispriced security to the passive portfolio. To answer the research question a quantitative method approach has been chosen. The method is built on secondary financial data and statistical analysis.

2.1 Modern Portfolio Theory

Markowitz (1952) introduces an expected return – variance of returns rule (E-V rule) that recognizes that an investor might be willing to give up some units of expected return to reduce the variance of returns and vice versa. Markowitz divides the portfolio selection problem into three parts: 1) Determining the expected return, variance of expected returns and covariance between assets. 2) Constructing an efficient set of portfolios based on these inputs. 3) Choosing a single portfolio based on the investor’s risk aversion (Sharpe, 1963).

Consistent with the Modern Portfolio Theory's focus on diversifying as far as possible to exploit low variances in order to minimize portfolio variance, Bekkers et al. (2009) suggests that adding real estate, commodities and high yield would create the optimal risky portfolio. Marot et al (2017) examine whether P2P is an attractive asset class, looking at the US P2P market, and only use stock and bond indices, with a 60% weight on stocks and a 40% weight on bonds. Thus, in spite of Bekkers et al’s recommendation of the inclusion of more asset classes to obtain the appropriate benchmark portfolio, we choose to use the conventional approach as Marot et al (2017) of defining the benchmark portfolio as consisting of stocks and bonds in order to simplify the methodology. The benchmark portfolio is specified in detail in data description section 3.2.

Limitations of the theory

Modern Portfolio Theory makes some simplifying assumptions, which we also use. One of these assumptions is that the historic covariances matrix is a good estimate of the future covariance matrix. However, this assumption is criticized by Ledoit and Wolf (2004) as outliers affect the sample covariance matrix but are unlikely to affect the future covariance matrix.

A second problem with mean variance-optimization according to Hurley and Brimberg (2015) is that the parameter estimates have a significant impact on the results. That can lead to either undervaluation or overvaluation of the mean variance portfolio that is out of sample.

Now that we have briefly described the theoretical background of Modern Portfolio Theory we will develop a methodology that is based on it, which we will present below. We use four steps which are described in detail below.

Step 1: Estimating expected returns, volatilities and correlations

Since we use historical data and do not base our methodology on extensive forecast modelling, we will use the simplifying assumption that expected returns, volatilities and correlations can be approximated by historical returns, volatilities and correlations. Both Markowitz (1952) and Sharpe (1963,1964) emphasize the importance of the covariance between assets and that minimizing the covariance between the securities is a crucial step in achieving efficient diversification. That is the reason why it is important to not only estimate the expected returns and volatilities that are inputs to the Sharpe ratio but also the correlations.

First, we estimate the expected returns, volatilities and correlations for the P2P asset class, the three stock indices and the three bond indices, which are specified in data description. We use a time frame of Jan 1 2013, to Dec 31, 2017 and calculate monthly returns11 for all three asset classes. This allows us to use 60 observations to estimate the correlation between the P2P asset class, the stock index and the bond index. Since the volatilities are calculated on a monthly basis we use the transformation factor $\sqrt{12}$ to obtain the annual volatility.

The expected returns are approximated by the 5-year annualized historical returns for the equity and bond asset classes. The 5-year returns of the equity indices and the bond indices are calculated as

$$\frac{Closing\ price_{Jan\ 1,\ \ 2018}}{Opening\ price_{Jan\ 1{,}2013}} - 1$$

Then the annualized return for the bond and stock asset class is calculated as:

$$(1 + 5year\ return)^{\left(\frac{1}{5}\right)} - 1$$

The monthly returns for the P2P asset class are calculated differently. Since the entire investment in the P2P loans is made up front, it generally takes more than a year until the repayments exceed the initial investment and a positive return can be said to have been generated in the traditional sense. We reconcile this issue by using an extrapolation technique. We use the repayments each month and compare them to an adjusted monthly principal. Thus, the return each month is calculated as:

$$Return_m = \frac{Monthly\ repayment_{l,n}}{Monthly\ principal_i} - 1$$

where $\in N,\ 1 \leq m \leq 60$, l is loan l, and n is the n_{th} repayment that the borrower of loan l has made in month m.

The adjusted monthly principal is calculated in a way that resembles accrual accounting:

$$Monthly\ principal_i = \ Amount_i\ /Loan\ duration\ _i.$$

For instance, if an investor invests € 1,000 in a loan that has a duration of 10 months and pays 12% annual interest, then the adjusted monthly principal is €100. If both the principal payment matches the monthly principal and the interest is repaid in the first month, then the return in that month for that loan is $\frac{100+10}{100} - 1 = 10\%$. It is important to note that this is not a monthly return, but rather an extrapolated return for the entire loan based on the pattern from the estimation month. To calculate the entire asset class' return in a given month we use the following equation:

$$Return_m = \frac{\sum_l Repayment_l}{\sum_l Monthly\ principal_l} - 1$$

Then the extrapolated P2P portfolio returns each month are correlated with the monthly returns of the equity and bond indices to obtain the correlation matrix. The volatility that is calculated for the P2P asset class is based on 60 extrapolated returns which are based on monthly estimates. That means that the estimated volatility describes the volatility for the aggregate loan portfolio over the entire loan duration. Since the average loan duration in our sample was 22.83 months, this means that the initially estimated volatility for the P2P asset is on approximately 23 months basis. We thus approximate annual volatility by using the following transformation:

$$Annual\ volatility_{P2P} = \frac{Estimated\ volatility_{P2P}}{\sqrt{Average\ loan\ duration\ (years)_{P2P}}}$$

The expected annual return of the P2P portfolio is computed using similar reasoning and a similar transformation:

$$Expected\ return\ P2P = Median\ return\ P2P\ (m \in N, 1 \leq m \leq 60)$$
$$= \frac{30\ th\ largest\ return + 31\ st\ largest\ return}{2}$$

Then we transform the expected return into annual form using the following transformation:

$$Expected\ annual\ return\ P2P = \frac{Expected\ return\ P2P}{Average\ loan\ duration\ (years)}$$

Once the expected returns, volatilities and correlations have been estimated, the next step is to determine the risk-free rate. We will use the average of the ten-year Estonian government bond yields 2013 to 2017 as the risk-free rate. The reason why we choose an Estonian risk-free asset is partly because Bondora is primarily an Estonian P2P platform.

Step 2: Constructing the minimum variance frontier

From Step 2 we use three different scenarios to obtain the results. Scenario 1 is the most conservative scenario which has the most constraints, while scenario 3 is the best-case scenario with the fewest constraints. We use different scenarios to briefly examine how sensitive our results are to the assumptions about the benchmark portfolio. The scenarios are as follows:

1. The benchmark portfolio is a 60 % equity portfolio and a 40% bond portfolio with equal weights on all the equity indices
2. The benchmark portfolio will be found numerically by solving the portfolio optimization problem with the constraint that the weights on all the equity indices are the same. Thus, under this scenario the benchmark portfolio could theoretically consist entirely of stocks or bonds.
3. This scenario only looks at what composition of portfolio performed optimally during the sample time horizon, without relating to a benchmark portfolio.

Having obtained the expected return, volatility, correlations and risk-free rate, we construct the minimum variance (efficient) frontier that consists of all the portfolios that minimize the variance for a given expected return target, or equivalently maximize the expected return for a certain level of variance. Algebraically this is equivalent to calculating: min $Var\left(\tilde{r}_p\right) = Var\left(\sum_{i=1}^{N} w_i \widetilde{r_i}\right)$ such that $E\left(\tilde{r}_p\right) = E\left(\sum_i^N w_i \tilde{r}_i\right) = \sum_i^N w_i E(\tilde{r}_i) = \bar{r}$ for $\forall \bar{r} \in N$ (Bodie et al. 2014).

Step 3. Finding the optimal risky portfolio

Once the efficient frontier is obtained we run the portfolio optimization problem by maximizing (Bodie et al. 2014):

$$\max_{w}\left(\frac{E(\tilde{r}_p) - r_f}{\sigma(\tilde{r}_p)}\right)$$

The financial assets considered in the optimization problem are the following: Three equity indices: S&P 500 in US, the FTSE 100 in the UK and the Nikkei 225 in Japan and three bond indices, which are the iShares aggregate bond fund ETF (AGG) in the US, the EURO STOXX 50® Corporate Bond Index and the ABF Pan Asia bond index.

The process of finding the optimal risky portfolio is slightly different for the different scenarios. All the scenarios have the general constraint that no-short selling is allowed and that borrowing at the risk-free rate is not allowed, which means that the portfolio weights have to sum up to one, which can algebraically be expressed as follows:

$$\sum_{i}^{7} w_i = 1, \;\; 0 \leq i \leq 1 \; \forall i$$

Besides the general constraints, scenario 1 and scenario 2 also have scenario-specific constraints. The scenario 1 specific constraint is that the stock-to-bond ratio is 1.5 and that the weight on the three different equity indices is the same, which algebraically can be expressed as follows:

$$W_{S\&P\ 500} = W_{FTSE\ 100} = W_{NIKKEI\ 225}, \qquad W_E = 1.5 * W_B$$

The scenario 2 specific constraint is that three different equity indices are equally weighted which mathematically can be expressed as follows:

$$W_{FTSE} = W_{NIKKEI} = W_{S\&P\ 500}$$

We will subsequently verify that the portfolio that we obtain belong to the minimum variance frontier.

Step 4. Describing investor allocation decisions as a function of risk aversion

Elton and Gruber (1997) describe how the optimal risky portfolio is the same for all investors when there is a risk-free asset. This is the two-fund separation theorem. The implication of the fund-separation theorem is that investors will not vary the composition of the risky portfolio according to their risk preferences but instead the proportions allocated to the risky portfolio and the risk-free asset.

We use the standard utility function $U\ (r) = E\ (r) - \frac{A}{2} * Var\ (r)$. The two-fund separation theorem states that all investors will hold the same risky portfolio which is the optimal risky portfolio that offers the best trade-off between return and risk. Thus, what investors will modify to obtain the portfolio that suits their risk attitude is the allocation between the risk-free asset and the optimal risky portfolio. Mathematically the problem is to maximize (Bodie et al. 2014).:

$$\max U(\tilde{r}) = \max(E(\tilde{r}) - 0.5A * \sigma^2(\tilde{r})) = \max\left(r_f + w * \left[E(\tilde{r}_p) - r_f\right] - 0.5A * w^2\sigma^2(\tilde{r}_p)\right)$$

Taking the derivative with respect to w and setting the derivative equal to zero yields:

$$\left[E(\tilde{r}_p) - r_f\right] - A * w\sigma^2(\tilde{r}_p) = 0$$

Thus, the optimal weight for an investor with risk aversion A is (Bodie et al. 2014):

$$w^* = \frac{1}{A} * \frac{\left[E(\tilde{r}_p) - r_f\right]}{\sigma^2(\tilde{r}_p)} = \frac{1}{A * \sigma(\tilde{r}_p)} * S_p$$

Where S_p is the Sharpe ratio of the portfolio which is defined as follows:

$$S_p = \frac{E[r_p) - r_f}{\sigma}$$

2.2 Treynor-Black Model

The Treynor-Black model assumes the existence of two portfolios: a passive market portfolio and an active portfolio consisting of securities which have an alpha. Elton and Gruber (1997) claim that if CAPM holds the weight that should be placed on an additional security added to a well-diversified portfolio is proportional to the ratio of the security's excess return over the extra variance incurred.

Sharpe (1963) assumes that the returns of different securities are uncorrelated expect for their mutual correlation with a common factor. He formulates this algebraically as: $R_i = A_i + B_i I + C_i$ where he defines A_i and B_i as parameters and C_i as a random term with expected value 0 and variance Q_i and I as some index. Sharpe called this the diagonal model and it has a similar structure as CAPM with B_i as β_i, as C_i as ε_i and A_i corresponding to the α. We will use the CAPM in the Treynor-Black model.

The steps we will use in the Treynor-Black Model to be able to answer our research question, are the following:

Definition of the passive portfolio

We will consider three different proxies for the passive portfolio: FTSE 100, NIKKEI 225 and S&P 500. We use these three indices because it is common to use a broad stock market index as the market portfolio and we aim to consider how robust the weight recommendation for the P2P asset class is to the definition of the market portfolio. Out of these three different portfolios we construct three different scenarios when analyzing step 1-4.

Step 1: Estimating the monthly returns of the P2P asset class

The extrapolated monthly return on the P2P portfolio is calculated as follows:

$$Monthly\ return\ (P2P)_m = \left(\frac{Monthly\ repayment_m}{Monthly\ principal_m}\right)^{(1/Average\ loan\ duration_m)} - 1$$

where $Monthly\ principal_m = \frac{Amount_m}{Average\ loan\ duration_m}$ and m is the month, where $m \in N,\ 1 \leq m \leq 60$ and m=1 is the month between 1 January, 2013 and 1 February 2013 and m=60 is the month between 1 December, 2018 and 31 December, 2017. $Average\ loan\ duration_m$ is the arithmetic average of all loans that are still outstanding in month m and $Loan\ amount_m$ is the total sum of all the loans that are still outstanding in month m. The efficiency of this estimation technique depends on to what degree the principal payments are evenly distributed over the loan period.

Step 2: Running regressions of the excess returns of the P2P asset class on the excess returns of the passive portfolio to obtain the alpha and residual variance of the P2P asset class

Since we have three different definitions of the passive (market) portfolio, we run three different ordinary least squares regressions to determine the alpha and the residual risk of the P2P asset class. The regression we run is a specific variant of the standard CAPM regression:

$$r_{P2P} = r_f + \beta_{P2P}(r_m - r_f) + \alpha_{P2P} + \varepsilon_{P2P}$$

where r_f is the risk-free rate, which will be the 10-year UK government bond yield when the market portfolio is proxied by FTSE 100, the 10-year Japanese government bond yield when the proxy for the market portfolio is NIKKEI 225 and the 10-year US government bond yield when S&P 500 is considered a representation of the market portfolio. β_{P2P} is the sensitivity of the P2P asset class to the market portfolio, r_m is the return of the market portfolio, α_i is the alpha of the P2P asset class or as Treynor and Black call it, the independent return of the P2P asset class. ($\beta_i(r_m - r_f)$) is called the explained or systematic return of the P2P asset. ε_{P2P} is the residual standard deviation of the P2P asset class. r_m and r_f will have three different values in the three different regressions as the three regressions differ in their specification as to what constitutes the market portfolio. The three specific regressions are presented below:

Regression 1: $r_{P2P} - r_f(UK) = \alpha_{P2P} + \beta_{P2P}\left(r_{FTSE} - r_f(UK)\right) + \varepsilon_{P2P}$ where $r_f(UK)$ is the yield on the 10 year United Kingdom government bonds, r_{FTSE} is the monthly return on the FTSE 100 and ε_{P2P} is a random error term with expectation 0 and variance ε^2.

Regression 2: $r_{P2P} - r_f(Japan) = \alpha_{P2P} + \beta_{P2P}(r_{NIKKEI} - r_f(Japan)) + \varepsilon_{P2P}$ where $r_f(Japan)$ is the yield on the 10 year Japanese government bonds, r_{NIKKEI} is the monthly return on the NIKKEI 225 and ε_{P2P} is a random error term with expectation 0 and variance ε^2.

Regression 3: $r_{P2P} - r_f(US) = \alpha_{P2P} + \beta_{P2P}(r_{S\&P\,500} - r_f(US)) + \varepsilon_{P2P}$ where $r_f(US)$ is the yield on the 10 year United States government bonds, $r_{S\&P\,500}$ is the monthly return on the S&P 500 and ε_{P2P} is a random error term with expectation 0 and variance ε^2.

The regressions will be run on a monthly basis meaning that there will 60 observations. The risk-free rate, which is stated as a yearly yield each month is divided by 12 to obtain a quasi-monthly risk-free rate. The reason why the risk-free rate is transformed into a monthly basis is so that it can be compared with the monthly returns on the market portfolio and the extrapolated monthly return on the P2P portfolio.

Step 3: Estimating the monthly market risk premium and variance

The monthly market risk premium will be calculated as the arithmetic mean of the market risk premium each month from month 1 to 60. The market risk premium will be calculated as $r_m - r_f/12$ where r_m is the return in month m and r_f is the annual risk-free rate in month m.

Step 4: Using the alpha and residual variance of the P2P asset class as well as the monthly market risk premium and variance to calculate the weight on the P2P asset class

Using the Treynor-Black model we obtain the ratio invested in the active portfolio as: $w_A = \frac{w_0}{1+(1-\beta_A)w_0}$ where $w_0 = \frac{\alpha_A/\sigma^2{}_A}{(r_m - r_f)/\sigma^2{}_m}$ and $\sigma^2{}_A$ is the variance of the residuals in the regression.

Limitations of the model

According to Kane, Kim and White (2003) many renowned scholars do not think that most analysts have sufficient predictive ability to implement the model in the correct way. Furthermore, they point out that the forecast output of the model needs to be statistically tested.

Second limitation is that when estimating expected returns, we use CAPM but since it makes many simplifying and unrealistic assumptions it may lead to rather unrealistic results (Fama and French, 2004).

3 Data description

In this section, we give an overview of the loan dataset and repayments dataset that we use to investigate our research question. The section provides firstly an overview of P2P loan data that was gathered from Estonian P2P platform Bondora. The repayments data was gathered on 11 March 2018 and the loan data was gathered on 24 March 2018. Secondly, we give an overview on data that supports our benchmark portfolio. The data was gathered from investing.com on 29 April 2018.

3.1 P2P loan data

The original loan dataset contained 53,852 loans. However, we have trimmed the data to a certain extent, only focusing on Estonia and excluding Finland, Spain and Slovakia in which Bondora also operates. Furthermore, we removed observations with missing values to enable better forecasts. After data trimming we were left with a sample size of 4,835 loans. The repayment original dataset contained 696,710 repayments. We merged the loan dataset with the repayments dataset. Our final merged dataset contains 96,626 repayments.

Variables that we used in our datasets are described in Table 1 below.

Variable name	**Description**
A. Loan dataset	
Loan Id	A unique ID given to all loan applications
Amount	Amount the borrower received on the primary market
Loan duration	Current loan duration in months
B. Historic payments	
Loan Id	A unique number given to loan applicants
Date	Date when the payment was made
Principal repayment	The amount of principal repaid
Interest repayment	The amount of interest paid
C. Generated variables	
Total repayment	=Principal repayment + Interest Repayment
Monthly principal	=Amount / Loan duration

Table 1: Description of P2P loan portfolio variables

3.2 Benchmark portfolio data

The data for the benchmark portfolio components were collected from investing.com, for the time horizon between Jan 1, 2013 and Jan 1, 2018. The data for the Estonian risk-free rate was collected from knoema.com on April 13, 2018.

The benchmark portfolio will be defined slightly differently under above mentioned two theories. For the Modern Portfolio Theory, it will be a 60/40 equity-bond portfolio while for the Treynor-Black Model three different approximations for the benchmark portfolio will be made: FTSE 100, NIKKEI 225 and finally S&P 500. In order to achieve geographic diversification, we chose equity and bond indices both in Europe, North America and Asia. Table 2 contains the variables included in the downloaded files.

Name	**Description**
	A. Index variables
Date	The date for which the closing price and change are calculated
Price	The closing price at the given date
Change%	The change between the current closing price and the closing price a month ago in percent
	B. Generated variable
Change	=Change%/100
	C. Index ticker symbols
ABF	The ABF Pan Asia Bond Fund
AGG	The iShares Barclays Aggregate Bond ETF
EUR	The EURO STOXX 50® Corporate Bond Index
FTSE	The Financial Times Stock Exchange 100 Index
NIKKEI	The largest stock market index for the Tokyo Stock Exchange
S&P 500	Standard & Poor's 500 Index
	D. Market variables
Risk-free rate (EE)	The yield on 10-year Estonian government bonds
Risk-free Rate(UK)	The yield on 10-year UK government bonds
Risk-free Rate (JPN)	The yield on 10-year Japanese government bonds
Risk-free Rate(US)	The yield on 10-year US government bonds

Table 2. Description of benchmark portfolio variables

The Estonian risk-free rate is used in the Sharpe ratios in the methodology based on the Modern Portfolio Theory. The UK risk-free rate, the Japanese risk-free rate and the US risk-free rate are used in regressions 1, 2 and 3, respectively, in the Treynor-Black Model regression of the P2P excess returns on the FTSE, NIKKEI and S&P 500 excess returns, respectively.

4 Results and discussion

In this section we will present our empirical results and discuss them. First, we present the results from the methodology based on the Modern Portfolio Theory and then we present the results from the methodology based on the Treynor-Black model. In the end of the approaches we compare the results obtained to existing literature and critically evaluate the results.

4.1 Modern Portfolio Theory

Below, we present the results from the methodology that is based on the Modern Portfolio Theory. We will start by presenting the results for the estimated expected returns, volatilities and correlations. Then present the efficient frontiers for each of the three scenarios. Subsequently we will show the composition of the optimal risky portfolio for all the scenarios and finally we will show how investors' risk aversion affect their allocation between the risk-free asset and the optimal risky portfolio in each separate scenario.

Step 1 Estimating expected returns, volatilities and correlations

Below, we provide the expected returns and volatilities of the seven assets. Then we will show the correlation matrix for the seven assets.

Table 3 shows that AGG had a negative realized return of –0.4%. It was however the least volatile asset on an individual basis. NIKKEI had the highest realized return of 15.7% per annum but also had the highest volatility. The P2P asset class a had a fairly high return of 8.2%, which was more than the worst performing equity index.

Asset	Expected return	Annual volatility
ABF Pan Asia	1.9%	9.0%
AGG Bond	-0.4%	3.1%
EUR STOXX	6.0%	14.1%
NIKKEI 225	15.7%	16.2%
FTSE 100	3.7%	10.1%
S&P 500	13.5%	9.5%
P2P	8.2%	13.2%

Table 3. Expected returns and volatilities for the seven assets

Table 4 shows the correlations between the seven different assets considered in the analysis. Table 4 provides information that the iShares Barclays aggregate bond ETF and the P2P asset class are those that are the least correlated with the other assets, thus providing the largest diversification benefits. Conversely, the EURO STOXX 50® Corporate Bond Index (EUR) and the S&P 500 are the assets that provide the smallest diversification benefits. Both of them have correlations with at least three other assets of at least 0.5. The highest correlation is between the ABF Pan Asia Bond Index and NIKKEI 225 of 0.65. This means that $0.65^2 = 42.25\%$ of the returns on the NIKKEI 225 can be explained by the returns of the ABF Pan Asia Bond Index. The smallest correlation is between the iShares Barclays aggregate bond fund ETF and the NIKKEI 225 and it amounts to -0.25. This might be explained by the fact that the assets constitute two different asset classes and are traded on markets that are very geographically distant. Two final noteworthy correlations are the 57% and 56% correlations between the S&P 500 and the FTSE 100 and NIKKEI 225. These are moderately high correlations that do not provide vast diversification benefits, at least compared to the diversification benefits that are obtained by including the AGG or the P2P portfolio.

	ABF	AGG	EUR	NIKKEI	FTSE	S&P 500	P2P
ABF	1.00	0.00	0.51	0.65	0.45	0.49	0.00
AGG	0.00	1.00	0.06	-0.25	0.32	-0.06	-0.06
EUR	0.51	0.06	1.00	0.59	0.61	0.63	0.01
NIKKEI	0.65	-0.25	0.59	1.00	0.24	0.57	-0.03
FTSE	0.45	0.32	0.61	0.24	1.00	0.56	-0.08
S&P	0.49	-0.06	0.63	0.57	0.56	1.00	-0.01
P2P	0.00	-0.06	0.01	-0.03	-0.08	-0.01	1.00

Table 4. Correlation matrix of the seven assets

Step 2: Constructing the minimum variance frontier

Below, we present the minimum variance frontiers for the three different scenarios and comment on the findings.

Scenario 1

As figure 1 demonstrates the global minimum variance portfolio in this scenario has a standard deviation of approximately 5%. The maximum attainable expected return is approximately 9% but that comes at a price of more than 5 percentage points higher volatility than in the case of the global minimum variance portfolio. The fact that the curve is bowl-shaped is associated with the fact that due to low covariance between the least risky asset and second least risky asset, it is possible to achieve lower portfolio variance and higher expected return by combining them rather than only including the least risky asset in the portfolio.

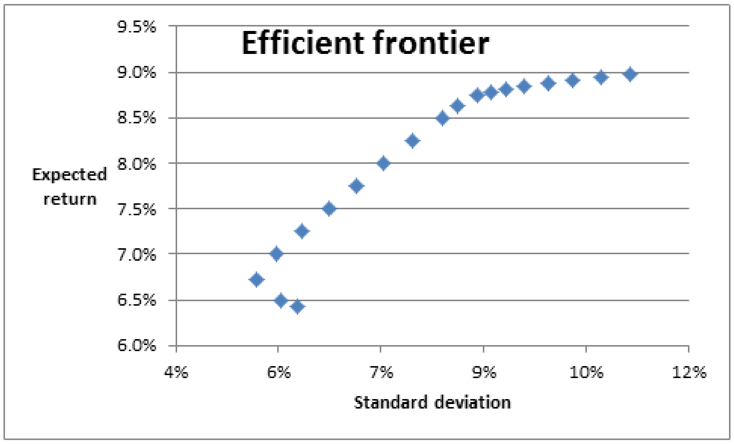

Figure 1. Minimum variance (efficient) frontier for scenario1

Scenario 2

Figure 2 demonstrates that the global minimum variance portfolio (the point on the curve the farthest to the left) has a volatility of approximately 3%. The slope of the efficient frontier is fairly constant between expected returns of 4% and 10%. Beyond expected returns of 10% figure 2 demonstrates that the volatility is increasing relatively quickly, which could suggest that those efficient portfolios are entirely made up of equities and thus more volatile.

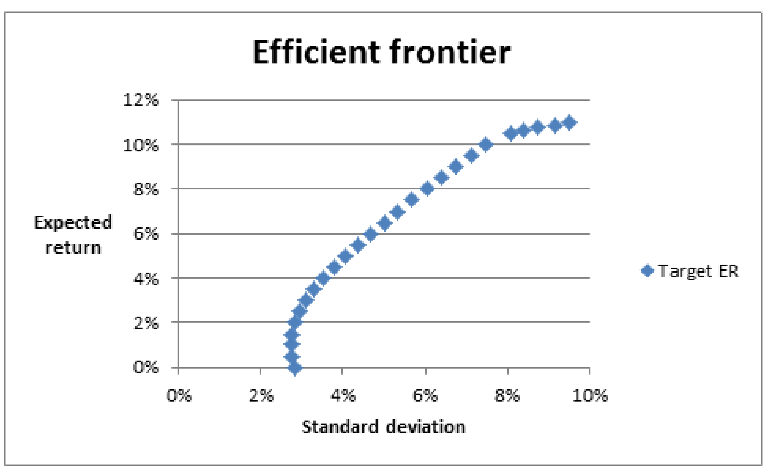

Figure 2. Minimum variance (efficient) frontier for scenario 2

Scenario 3

The minimum variance portfolio has a volatility of approximately 3%, which is demonstrated in figure 3. The maximum attainable expected return is approximately 15%. The riskiest portfolio has a volatility of circa 15%. The risk appears to be increasing relatively fast for each incremental 10th of a percentage point beyond expected returns of 12.5%, as figure 3 demonstrates by the flattening slope of the curve above expected returns of 12.5%.

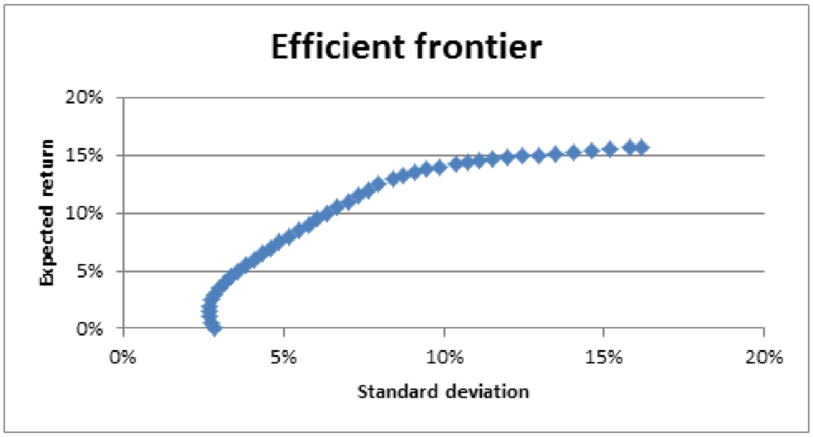

Figure 3. Minimum variance (efficient) frontier for scenario 3

Step 3: Finding the optimal risky portfolio

Scenario 1.

The benchmark portfolio that had the optimal Sharpe ratio during the sample period as table 5 describes. The optimal portfolio consists of 40% AGG, 20% NIKKEI, 20% FTSE and 20% S&P 500. Interestingly, the bond index that makes up the 40% bond portion is the bond index with the lowest return. It even has a negative expected return of -0.42% per annum. However, it has by far the lowest volatility of all the assets, with 3.07% annual volatility. As Table 4 presents, AGG alongside the P2P asset class is the asset that has the lowest correlation with the other assets. Thus, it seems that the reason the AGG bond is included in the optimal risky benchmark portfolio despite its negative return is its low volatility and low covariance with other assets.

The optimal benchmark portfolio has an expected return of 6.4% and a volatility of 5.8% and a Sharpe ratio of 0.99, which table 5 describes.

Asset	Weight
ABF Pan Asia	0.00%
AGG Bond	40.00%
EUR STOXX	0.00%
NIKKEI 225	20.00%
FTSE 100	20.00%
S&P 500	20.00%
P2P	0.00%
Portfolio ER	6.42%
Portfolio volatility	5.79%
Risk-free rate	0.69%
Sharpe ratio	0.99

Table 5. Expected return and volatility of the benchmark portfolio in scenario 1

The effects of introducing the P2P asset class into the portfolio optimization problem are illustrated in table 6. The P2P asset class has a 21.19% weight in the optimal risky portfolio in scenario 1.

There is a substitution effect that leads to circa an 8.5 percentage point reduction in the weight of AGG in the optimal risky portfolio and a reduction of circa 4.2 percentage points in each of NIKKEI 225, FTSE 100 and S&P 500. The portfolio's expected return increases from 6.4% to 6.8% and its volatility decreases from 5.8% to 5.2%. These two effects combined manifest in an increase in the Sharpe ratio from 0.99 to 1.17. The optimal risky portfolio only contains one of the three bond indices, but that bond index is the asset with the largest individual weighting in the portfolio. The P2P asset class has a 21% weight in the optimal risky portfolio in this scenario, illustrated in table 6.

Asset	Weight
ABF Pan Asia	0.00%
AGG Bond	31.53%
EUR STOXX	0.00%
NIKKEI 225	15.76%
FTSE 100	15.76%
S&P 500	15.76%
P2P	21.19%
Portfolio ER	6.80%
Portfolio volatility	5.21%
Risk-free rate	0.69%
Sharpe ratio	1.17

Table 6: Optimal risky portfolio for scenario 1

Scenario 2.

Scenario 2 relaxes the constraint from scenario 1 that the equity-to-bond ratio remain 1.5 in the optimal risky portfolio. The new composition of the portfolio is provided in table 7.

Asset	Weight
ABF Pan Asia	0.00%
AGG Bond	0.00%
EUR STOXX	0.00%
NIKKEI 225	33.33%
FTSE 100	33.33%
S&P 500	33.33%
P2P	0.00%
Portfolio ER	10.98%
Portfolio volatility	9.52%
Risk-free rate	0.69%
Sharpe ratio	1.08

Table 7. Benchmark portfolio in scenario 2

The benchmark portfolio in scenario 2 that has the maximum reward-to-risk ratio is an equally-weighted 100% equity portfolio with expected return of 10.98% and volatility 9.52% and a Sharpe ratio of 1.08.

The optimal risky portfolio in scenario 2 has a 28.74% weight on the P2P asset class and the remainder of the portfolio is made up entirely by equities. It has an expected return of 10.18% and volatility 7.62%. Its Sharpe ratio is 1.25. Compared to the benchmark portfolio it has 0.8 percentage points lower return, 1.9 percentage points lower volatility and a Sharpe ratio that is 0.17 units higher.

Asset	Weight
ABF Pan Asia	0.00%
AGG Bond	0.00%
EUR STOXX	0.00%
NIKKEI 225	23.75%
FTSE 100	23.75%
S&P 500	23.75%
P2P	28.74%
Portfolio ER	10.18%

Portfolio volatility	7.62%
Risk-free rate	0.69%
Sharpe ratio	1.25

Table 8. Composition of optimal risky portfolio in scenario 2.

Both optimizations thus far have yielded fairly extreme results from a traditional portfolio theory perspective that emphasizes the importance of diversifying as far as possible and typically implemented that recommendation by pointing towards a portfolio consisting of both stocks and bonds. It is a potential weakness in our results that the optimal risky portfolio without the P2P asset class included in the analysis consists of 100% equities. This could be attributed to the time horizon being fairly short. Furthermore, both the S&P 500 and NIKKEI 225 had abnormally high returns from a historical perspective (13.5% and 15.7% respectively) while the FTSE 100 had weak returns of 3.7% annually. The S&P 500 was also very stably drifting upwards with monthly volatility of only 2.75% and annual volatility of 9.52%. All these factors combine to present a risk of biased estimates and overfitting.

Scenario 3

We find that the optimal risky portfolio does not consist of any fixed income securities, but rather 76% equities and 24% P2P. Specifically the ORP is a three-asset portfolio that has a 67.61% weight on S&P 500, 23.64% weight on the P2P asset class and 8.74% weight on the NIKKEI 225. It has an expected return equal to 12.45% and a volatility of 7.93%

We subsequently verify that this portfolio does indeed belong to the efficient frontier, by first changing the weights to 20% NIKKEI 225, 30% S&P 500 and 50% P2P (arbitrarily chosen). Then we set the expected return target equal to 12.45% and minimize the portfolio variance. We obtain the same weights as before, and a volatility of 7.93%. Thus, the ORP has a Sharpe ratio of $\frac{12.45\%-0.69\%}{7.93\%} = 1.48$, which is presented in table 9.

Asset	Weight
ABF Pan Asia	0.00%
AGG Bond	0.00%
EUR STOXX	0.00%
NIKKEI 225	8.75%
FTSE 100	0.00%
S&P 500	67.61%
P2P	23.64%
Portfolio ER	12.45%
Portfolio volatility	7.93%

Risk-free rate	0.69%
Sharpe ratio	1.48

Table 9: Optimal risky portfolio with P2P in scenario 3

For comparative purposes, we run the same optimization of the risky portfolio without the P2P asset class and then find that the ORP comprises 89.36% S&P 500 and 10.63% NIKKEI 225. It has an expected return of 13.75% and a volatility of 9.58%. Its Sharpe ratio is $\frac{13.75\%-0.69\%}{9.58\%} = 1.36$. The results are presented in table 10.

Asset	**Weight**
ABF Pan Asia	0.00%
AGG Bond	0.00%
EUR STOXX	0.00%
NIKKEI 225	10.63%
FTSE 100	0.00%
S&P 500	89.37%
P2P	0.00%
Portfolio ER	13.75%
Portfolio volatility	9.58%
Risk-free rate	0.69%
Sharpe ratio	1.36

Table 10: Optimal risky portfolio without P2P in scenario 3

Step 4: Describing investor allocation decisions as a function of risk aversion

Scenario 1

Figure 4 depicts how investors with different risk aversion levels choose to allocate their funds between the optimal risky portfolio and the risk-free asset. Even investors with relatively high risk aversion (for example A=10, where A is the risk aversion parameter) derive maximum utility by allocating all their funds to the optimal risky portfolio. This may be due to low volatility in the optimal risky portfolio, a low risk-free rate and/or a high market returns.

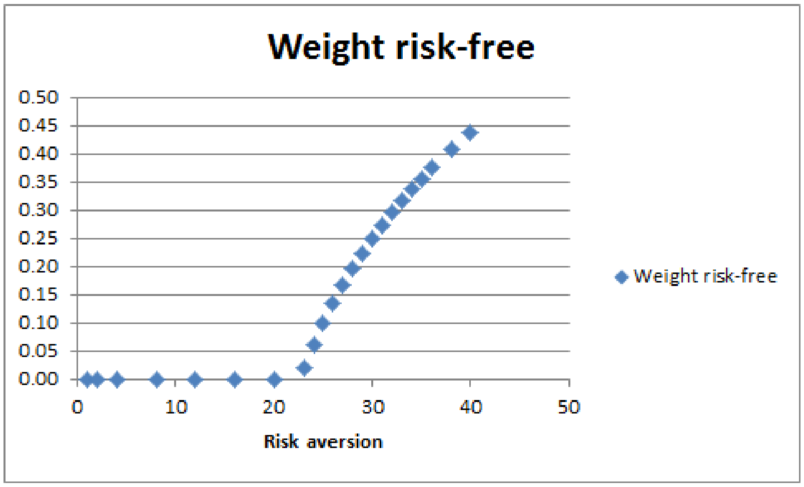

Figure 4. Investor allocation decisions as a function of risk aversion for scenario 1

Scenario 2.

Interestingly, compared to figure 4, the minimum risk aversion level for which the weight in the risk-free rate is positive is lower, even though the Sharpe ratio of the optimal risky portfolio in scenario 2 is higher than the Sharpe ratio in scenario 1. This is most likely due to the fact that the optimal risky portfolio in scenario 2 has both higher expected return and variance than the optimal risky portfolio in scenario 1 and very risk-averse investors put more emphasis on low variance than high expected returns.

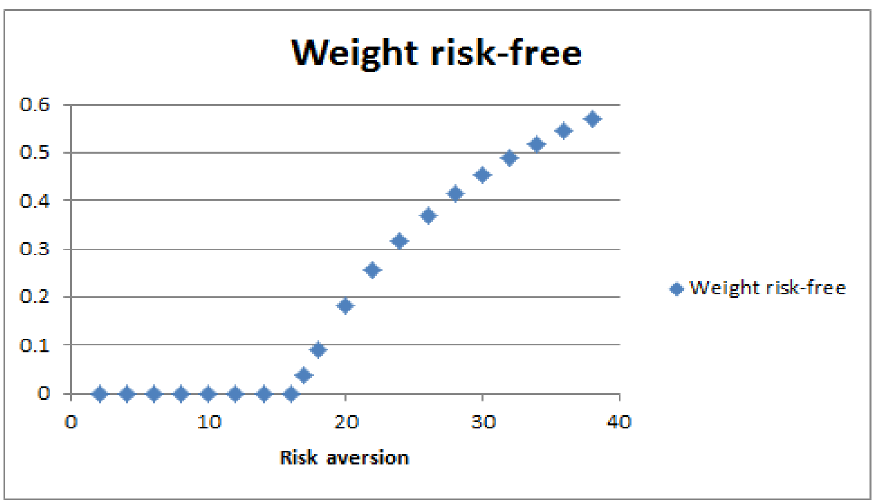

Figure 5. Investor allocation decisions as a function of risk aversion for scenario 2

Scenario 3

Figure 6 shows the allocation between the risk-free asset and the optimal risky portfolio is affected by the investor's risk aversion. Typically, it is assumed that the median investor has a risk aversion of 2. Due to the fact that the optimal risky portfolio had a relatively low volatility of 7.93% and a high return of 12.45% while the risk-free asset had a low return of 0.69% investors with risk aversion as high as 18 invest all their wealth in the optimal risky portfolio.

Figure 6. Allocation decisions as a function of risk aversion for scenario 3

Summary results from the Modern Portfolio Theory

The Modern Portfolio Theory yielded the results that the weight on the P2P asset class in the optimal risky portfolio was 21% in scenario 1, 29% in scenario 2 and 23% in scenario 3. The benefit of including the P2P asset class in the international portfolio was an increase in the Sharpe ratio from 0.99 to 1.17 in scenario 1, from 1.08 to 1.25 in scenario 2 and from 1.36 to 1.48 in scenario 3. This is consistent with the Modern Portfolio Theory's emphasis on diversifying as far as possible. Marot et al. (2017) also found that including the P2P asset class to a 60-40 equity-bond portfolio could increase the Sharpe ratio, specifically they found that the P2P asset class had a 16% weight in the optimal risky portfolio which had a Sharpe ratio of 5.72. Furthermore, they found that the P2P asset class had an annual volatility of 2.7% compared to our estimate of 13.2%. Thus, we consider our results relatively conservative in comparison with the scarce previous empirical evidence on the subject.

4.2 Treynor-Black Model

Below, we present the empirical results from the methodology that is based on the Treynor-Black Model. We have three different scenarios with three different definitions of the passive portfolio. First, we will present our estimates of the monthly returns for the P2P asset class, which is a common step for all three scenarios. Then we will present the results for the scenario with FTSE as the passive portfolio. We begin with step 2 for FTSE, then we present the results for steps 3 and 4 for FTSE. Thereafter we continue with steps 2-4 for NIKKEI and we conclude the Treynor-Black Model empirical section with steps 2-4 for S&P 500

Step 1: Estimating the monthly returns of the P2P asset class

Table 11 describes that the mean monthly return was 0.45% and the standard deviation was 0.64%.

Descriptive statistics P2P monthly returns	
Mean	0.45%
Standard Error	0.08%
Median	0.50%
Standard Deviation	0.64%
Sample Variance	0.00%
Kurtosis	5.34
Skewness	-1.28
Range	4.28%
Minimum	-2.34%
Maximum	1.94%
Sum	27.26%
Count	60
Confidence level (95.0%)	0.164%

Table 11: Descriptive statistics P2P monthly returns

Scenario 1: FTSE 100 is the passive portfolio

The regression result in Table 12 presents that the P2P asset class had a statistically significant alpha at the 5% significance level, with a lower 95% bound of 0.15%. The point estimate for the alpha is 0.31% per month. The beta coefficient is estimated at -0.015, but it is not statistically significant. The upper 95% bound for the beta value is 0.04.

SUMMARY OUTPUT

Regression statistics	
Multiple R	0.0699
R Square	0.0049
Adjusted R Square	-0.0123
Standard Error	0.0061
Observations	60

ANOVA

	df	SS	MS	F	Significance F
Regression	1	0.0000	0.0000	0.2851	0.5954
Residual	58	0.0022	0.0000		
Total	59	0.0022			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	0.0031	0.0008	3.9000	0.0003	0.0015	0.0047
X variable 1	-0.0146	0.0274	-0.5340	0.5954	-0.0694	0.0402

Table 12. Regression of P2P excess returns on FTSE 100 excess returns using the 10-year UK government bond yield as the risk-free rate.

Appendix table 1 provides that the monthly market risk premium is 0.346%. Appendix table 2 illustrates the variance of the market returns, which is 0.085%

First the initial weight of the active portfolio is calculated as: $\frac{\alpha_A/\sigma^2{}_A}{(r_m - r_f)/\sigma^2{}_M}$ From the regression above it is calculated that $\alpha = 0.31\%$. Using the residual output the residual variance is calculated to be $3.675\ldots{*}10^{-5}$. Using the results from above for the monthly market risk premium and monthly market variance the initial weight (w_0)
on the P2P portfolio (before rebalancing to retain constant exposure to market risk) is thus:

$$\frac{\frac{0.31}{0.003675}\%}{\frac{0.346}{0.085}\%} \approx \frac{84.35}{4.07} = 20.72$$

Then using the rebalancing equation yields that the final weight on the active portfolio, i.e. the P2P asset class is:

$$w_A = \frac{w_0}{1+(1-\beta_A)w_0} = \frac{20.72}{1+\big(1-(-0.0146)\big)*20.72} = \frac{20.72}{1+1.0146*20.72} = \frac{20.72}{1+21.022} = \frac{20.72}{22.022} \approx 94\%$$

The weight on the market portfolio is simply: $1 - w_A \approx 1 - 0.94 = 6\%$

Thus, using the Treynor-Black model on our dataset using FTSE 100 as the market portfolio suggests that the P2P portfolio should have a weight of 94% and the FTSE 100 a weight of 6%.

Scenario 2: NIKKEI 225 is the passive portfolio

The regression results are provided in table 13, which presents that the P2P asset class has a statistically significant alpha at the 5% significance level, with a lower 95% bound of 0.28%. The point estimate for the alpha is 0.44% per month. The beta coefficient is estimated at -0.013 but it is statistically insignificant with a 95% upper bound of 2.27%

SUMMARY OUTPUT

Regression statistics	
Multiple R	0.0931
R Square	0.0087
Adjusted R Square	-0.0084
Standard Error	0.0063
Observations	60

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.0000	0.0000	0.5068	0.4794
Residual	58	0.0023	0.0000		
Totalt	59	0.0023			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0.0044	0.0008	5.3052	0.0000	0.0028	0.0061
X variable 1	-0.0125	0.0176	-0.7119	0.4794	-0.0478	0.0227

Table 13. Regression of P2P excess returns on NIKKEI 225 excess returns using monthly data of 10-year Japanese government bond yield

The alpha is estimated in the regression and the point estimate is 0.44% per month. The residual variance was calculated using the sample variance of the residual output from the regression and amounted to: $3.89712 * 10^{-5}$. We also use the values for the market risk premium from Appendix table 3, $r_m - r_f = 1.025\%$ and the market variance from appendix table 4, $\sigma^2{}_m = 0.218\%$. Thus

$$w_0 = \frac{\alpha_A/\sigma^2{}_A}{(r_m - r_f)/\sigma^2{}_M} = \frac{\frac{0.44}{0.0038912}\%}{\frac{1.025}{0.218}\%} \approx \frac{112.9}{4.702} = 24.01$$

Then to rebalance the portfolio to maintain constant market risk exposure we use $w_A = \frac{w_0}{1+(1-\beta_A)w_0} = \frac{24.01}{1+(1-(-0.0125)*24.01} = \frac{24.01}{1+1.0125*24.01} = \frac{24.01}{1+24.310} = \frac{24.01}{25.31} = 96\%$

The remainder that is invested in the market portfolio is calculated as: $w_m = 1 - w_A = 1 - 0.96 = 4\%$

Thus, it is calculated that under the Treynor-Black model the weight that should be put on the P2P asset class is 96% and the weight that should be put on NIKKEI 225 is 4%.

Scenario 3: S&P 500 is the passive portfolio

Table 14 presents the results of the regression of P2P excess returns of S&P 500 excess returns. The alpha is statistically significant at the 5% level with a t-stat of 3.24 and a p-value of 0.002. The point estimate for the alpha is 0.28% per month, and the 95% confidence interval is between 0.11% and 0.45%. We will use the point estimate for the alpha of 0.28% in the Treynor-Black Model. We will also use the point estimate for the beta of -0.0107 even though the beta is statistically insignificant at the 5% level.

SUMMARY OUTPUT

Regression statistics	
Multiple R	0.0468
R Square	0.0022
Adjusted R Square	-0.0150
Standard Error	0.0063
Observations	60

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	5.05826E-06	5.05826E-06	0.1271	0.7227
Residual	58	0.0023	3.97956E-05		
Totalt	59	0.0023			

	Coefficients	*Standard error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0.0028	0.0009	3.2395	0.0020	0.0011	0.0045
X variable 1	-0.0107	0.0299	-0.3565	0.7227	-0.0706	0.0492

Table 14: Regression of P2P excess returns on S&P 500 excess returns

Using the output from the regression it is possible to calculate the weights of the active portfolio (P2P asset class) and passive portfolio (S&P 500). First the initial weight of the active portfolio is calculated as: $\frac{\alpha_A/\sigma^2{}_A}{(r_m-r_f)/\sigma^2{}_M}$ From the regression output it is given that $\alpha_A = 0.28\%$ and from the residual output the residual variance is calculated as: $\sigma^2{}_A = (\sigma_A)^2 = 0.625\ldots^2 = 3.19\ldots * 10^{-5} = 0.00319\ldots\%$

From the appendix tables 5 and 6 the market risk premium and the variance of the market returns are retrieved. The monthly market risk premium is thus on average 0.913% while the market variance is 0.075%.

Using the values from above the initial weight on the active portfolio before rebalancing to maintain a constant beta (i.e exposure to market risk) is:

$$\frac{\frac{0.28}{0.00319}\%}{\frac{0.91}{0.075}\%} \approx \frac{87.77}{12.13} = 7.236$$

Then we use the rebalancing equation and find that the weight that should be invested in the active portfolio is:

$$w_A = \frac{w_0}{1 + (1 - \beta_A)w_0} = \frac{7.236}{1 + \big(1 - (-0.0107)\big) * 7.236} = \frac{7.236}{1 + (1.0107) * 7.236}$$

$$= \frac{7.236}{1 + 7.313} = \frac{7.236}{8.313} = 87\%$$

While the weight that should be invested in the market portfolio is $1 - w_A = 1 - 0.87 = 0.13 = 13\%$

Thus, using the Treynor-Black model on our dataset yields the conclusion that the P2P asset class should have an 87% weight while the S&P 500 should have a 13% weight.

Summary results from the Treynor-Black model methodology

The results from the Treynor-Black model are somewhat extreme, with weights on the P2P asset class of 86%, 94% and 96% depending on whether the S&P 500, the FTSE 100 or NIKKEI 225 is considered the market portfolio. There are several reasons why such a large share in P2P is recommended by the model.

Firstly, the model puts a large emphasis on alpha. Since all three regressions indicate that the beta is very small for the P2P asset class with 95% upper bounds of 4.02% in the first regression, 2.27% in the second regression and 4.92% in the third regression, the alpha or unexplained return of the P2P asset class becomes quite large. This may due to the fact that the emergence of P2P is a relatively new phenomenon or it may be because the profitability of P2P has been poor in the past as shown by Ceyhan et al (2011), Freedman & Jin (2011) and Klafft (2008). Finally, Marot et al. (2017) discuss how the central bank’s low interest rates might make P2P a good investment. That is, holding all variables constant a reduction of the risk-free rate raises the alpha which could be one reason why the P2P asset class exhibits monthly alphas of 0.31%, 0.44% and 0.28% in the three different scenarios.

5 Conclusion

We researched whether the Estonian P2P portfolio should be added to investment portfolio in order to achieve better risk-reward trade-off. We used two different approaches and three scenarios on both approach to provide an answer to the question. Our empirical results present that the weight on the P2P asset class under both theories and all three scenarios for each theory is greater than zero. Thus, our results suggest that the Estonian P2P asset class should be added to an international portfolio in order to achieve better risk-reward trade-off. However, it is important to remark that the dataset contains only five years data and for that reason no general conclusion can be made without further research.

Further limitations to our research are that we only focus on the P2P asset class in one country, Estonia which means that there may be country specific features that produces results in our study that possibly are not transferrable to other countries. Furthermore, the short time frame of 5 years which means that the results may be sensitive to differences in business cycles. We assume that the covariance between the P2P asset class and the equity and bond indices will remain low in the future as they were during our sample period, which is a general criticism of the mean-variance optimization approach in the Modern Portfolio Theory, as we describe in the limitations to the theory. The financial crisis of 2008 showed that default rates can become highly correlated in times of recession, which could be a significant risk for P2P lending. Furthermore, as described in the limitations to the theories the estimates of the future covariances matrix may be biased because of outliers.

The results from the Treynor-Black model present that the Estonian P2P asset class has alpha, but this may be because of the inefficiency of a single index model or because we are not comparing the Estonian P2P portfolio to the Estonian market portfolio but international market portfolios. A final limitation is that we only use data from one platform which both meant that our sample size was relatively small considering the number of months for which we needed to estimate returns and that our study does not capture potential inter-platform differences.

Future research

Due to the limitations described above our findings are not conclusive and further research is required to corroborate our findings. Furthermore, it is necessary to analyze the aggregate P2P asset class in more countries and do cross-country comparisons. It would also be interesting to research the question using more advanced portfolio theories as well as including more asset classes in the investment universe. As different platforms have different business models it could also be insightful to analyze multiple platforms' data to investigate the impact of the business model on the investment attractiveness of the P2P asset class.

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Appendix

Table 1: Descriptive statistics monthly excess returns of FTSE 100

Descriptive statistics FTSE 100 excess returns	
Mean	**0.346%**
Standard Error	0.376%

Note: The most relevant statistic in this table is the mean, which is used in scenario 1 in the Treynor-Black Methodology as the market risk premium.

Table 2: Descriptive statistics monthly returns of FTSE 100

Descriptive statistics FTSE 100 monthly returns	
Mean	0.346%
Standard Error	0.376%
Median	0.800%
Mode	0.800%
Standard Deviation	2.910%
Sample Variance	**0.085%**

Note: The most important statistic in this table is the sample variance, which is used in scenario 1 in the Treynor-Black Methodology as the market variance.

Table 3: Descriptive statistics monthly excess return NIKKEI 225

Descriptive statistics NIKKEI 225 excess returns	
Mean	**1.025%**
Standard error	0.601%

Note: The statistic that we use in our thesis from this table is the mean, which is used in scenario 2 of the Treynor-Black methodology as the market risk premium.

Table 4: Descriptive statistics monthly returns of NIKKEI 225

Monthly market risk premium NIKKEI 225

Descriptive statistics NIKKEI 225 monthly returns	
Mean	1.331%
Standard Error	0.603%
Median	1.575%
Mode	#MISSING!
Standard Deviation	4.669%
Sample Variance	**0.218%**

Note: The pertinent statistic in this table is the sample variance, which is used in scenario 2 of the Treynor-Black methodology as the market variance.

Table 5: Descriptive statistics monthly excess returns of S&P 500

Descriptive statistics S&P 500 excess returns	
Mean	**0.913%**
Standard Error	0.354%

Note: The key statistic in this table is the mean, which is used in scenario 3 of the Treynor-Black methodology as the market risk premium.

Table 6: Descriptive statistics monthly S&P 500 returns

Descriptive statistics S&P 500 monthly returns	
Mean	1.099%
Standard error	0.355%
Median	1.135%
Mode	0.050%
Standard Deviation	2.747%
Sample Variance	**0.075%**

Note: The crucial statistic in this table is the sample variance, which is used in scenario 3 of the Treynor-Black methodology as the market variance