

P2P LENDING

**AN INVESTOR'S PERSPECTIVE ON THE MEASUREMENT
OF RETURN AND FACTORS IMPACTING DEFAULT HAZARDS**

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P2P Lending

Abstract:

The emergence of peer-to-peer (P2P) lending platforms has caught the attention of researchers. However, limited attention has been directed toward the investors. This paper aims to explore and measure the components of P2P lending returns in Sweden. Using a data set provided by one of the leading P2P lending platforms we explore internal rates of return of three subsets of loans. Additionally, we utilize the Cox proportional hazard model to explore what drives the default of borrowers as it has a large effect on investor returns. We find that the existence of a credit loss fund has a vital impact on the return as well as that the hazard of default is significantly impacted by both hard facts such as interest rates but also by unverifiable information such as the purpose of the loan.

Keywords:

P2P Lending, Peer-to-Peer, IRR, Survival Analysis, Cox Model

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1. Introduction

The financial services industry serves as an intermediary between those who have financial means at their disposal, and those who are in need of funds. The role of financial intermediaries is to manage financial contracts used to pool funds, share risks and transfer resources. They are compensated for providing these services and the income generated from doing this measure the aggregate cost of financial intermediation (Philippon, 2015). The potential for cost reductions and more effective financial intermediation stemming from the rapid technological development around the turn of the millennium was believed to be high. However, the unit cost of financial intermediation in the US has stayed roughly the same since the beginning of the 20th century, which holds true even after controlling for the quality of the intermediation as shown by Philippon (2015). The cost of financial intermediation affects both firms who issue debt and equity as well as households who borrow money or use asset management services. These costs are often seen as a driving force in the emergence and development of P2P financing in line with the theory of financial intermediation (Allen & Santomero, 1997). As pointed out by Havrylchyk and Verdier in 2018, it is too early to compare cost-efficiency of traditional banks and P2P lending platforms. This is mainly because few P2P lending platforms have achieved scale efficiency and profitability at this point in time (Havrylchyk & Verdier, 2018). Although yet only in its earliest stages, online marketplaces have the potential to replace banks as the traditional intermediary by enabling the brokerage of consumer loans directly between borrowers and lenders. In this paper we intend to study the attractiveness of the peer-to-peer (P2P) lending market as an alternative investment to traditional financial instruments. Hence, our research question is:

How can returns on P2P loans be measured and what affects these returns in terms of attractiveness?

The attractiveness can be divided into two main components, risk and return, which together measure the overall attractivity. Return is the gains or losses resulting from an investment and it can be measured in multiple different ways. Risk on the other hand is the possibility that the actual return will be different from what was expected, at least in its most basic sense from an investor's perspective. The risk component can be divided into two sub-components, usually referred to as systematic and idiosyncratic risk, which in turn can be further fractionated. In the context of P2P lending, probability of default (PD) is the most significant risk whether it is driven by borrower specific characteristics or macroeconomic factors. We aim to contribute to a more nuanced view of the P2P lending market by using traditional methods for evaluating capital investments and applying them to this rather new concept of investing. The issue is analyzed using data from a Swedish

lending platform, hereafter referred to as the Lending Platform. Realized returns are calculated with the internal rate of return (IRR) method and a theoretical expected return is estimated based on the interest rate charged from the borrowers and the service fees. For the purpose of analyzing the PD component, we are performing a survival analysis based on the Cox proportional hazard model. However, both in terms of risk and return we are limited by the relative short period of time our data stretches over, as well as the general availability of data related to P2P lending on the Swedish market. Compared to i.e. listed stocks and bonds, data on P2P loans are not publicly available and as such requires the cooperation of specific companies. In contrast to the US market, where both Lending Club and Prosper offer to export loan data directly from their websites, the Swedish P2P lending companies offer a very limited quantity of publicly available data why the study is based merely on data provided by the Lending Platform. We find that the IRR of the loans is generally above our constructed benchmark return, indicating that the benchmark might be unrepresentative. Additionally, as a point of reference an average portfolio on the platform earns between 0.43% and 4.59% before taxes depending on assumptions regarding reimbursement for credit losses. Furthermore, we find a number of significant variables affecting the default hazard. As we expected, a higher interest rate and lower credit score increases the hazard. The results from the Cox proportional hazard model have elements in line with previous research but we also found variables with contradictory impact. For example, we found loan consolidation to have a positive impact on default probabilities rather than being a risk contributor. In the remainder of this section we present an introduction to P2P lending, while the rest of this study is structured as follows. In Section 2, we present previous literature related to P2P lending and how it is related to this paper. In section 3 the data set used for the purpose of our study is presented and described before we present our method of research in part 4. Section 5 presents our findings on a component basis together with an overall evaluation. Finally, in the last section, we offer some concluding thoughts together with suggestions for further research.

1.1. Peer-to-Peer Lending

Since starting in 2005, P2P lending has experienced rapid growth (Milne & Parboteeah, 2016). P2P lending platforms are online intermediaries that match borrowers with lenders. People wanting to borrow money either place requests for loans online, where private lenders bid to fund these in an auction-like process or are being funded immediately given that their loan application is accepted by the platform. Early on, the P2P lending system was seen as offering credit to people who would not gain access to it elsewhere. In recent years however the platforms have expanded their reach, targeting a wider audience of both borrowers and lenders. The benefits of peer-to-peer platforms could be summarized as follows: borrowers

gain from higher probability of getting a loan funded at lower interest rates than the banks can provide, while lenders gain from higher expected returns compared to a traditional savings account. For a brief discussion of potential benefits to investors, see Morse (2015). On the other hand, there are several disadvantages that should also be considered. Loan default is an important matter in P2P lending since individual investors bear the credit risk, rather than financial institutions specialized in dealing with such risks (Serrano-Cinca et al., 2015). Related to this matter is the question regarding the agency problems arising when intermediaries have no skin in the game, something Holmstrom & Tirole (1997) brought attention to with their study on an incentive model of financial intermediation. Keys et al. (2010) further studied how loan securitization lowered the incentives of banks to screen borrowers, eventually contributing to the financial crisis in 2008. In light of this, platform founders often claim to invest money in loans issued by their platforms and several operators have adopted a hybrid business model where they lend at least part of their own money to borrowers (Havrylchyk & Verdier, 2018). As for the Lending Platform, they use something they refer to as performance-based fees, meaning that they only collect the service fee from the lender when the borrower fulfils their obligations (). In China, known for its enormous shadow banking network¹, there is already what could be seen as an ongoing P2P lending crisis with several platforms collapsing (Hornby & Zhang, 2018).

1.2. The Platform Operating Model: An Investor Perspective

Many P2P lending platforms operate in a similar way, with fees being charged both from borrowers and investors, but how these fees are structured vary among different platforms (Berger & Gleisner, 2009). In this section a simplified example of the main characteristics of the Lending Platform's operating model is described from an investor's perspective.

Investor A would like to invest some of their disposable wealth in P2P lending. Suppose they are a retail investor which will not have time to actively manage their portfolio with regular frequency, leading to them choosing the Lending Platform's option 'Autoinvest'. Autoinvest is an automated investment account which spreads the money invested across a minimum of 40 to 125 loans depending on the size of the investment. The table below presents the relation between money invested and the minimum number of loans in the portfolio ().

¹ The shadow banking system is a term for the collection of non-bank financial intermediaries that provide services similar to traditional commercial banks but outside normal banking regulations. For further information, see e.g. (Ehlers, Kong, & Zhu, 2018).

Table 1: Number of loans in an Autoinvest portfolio

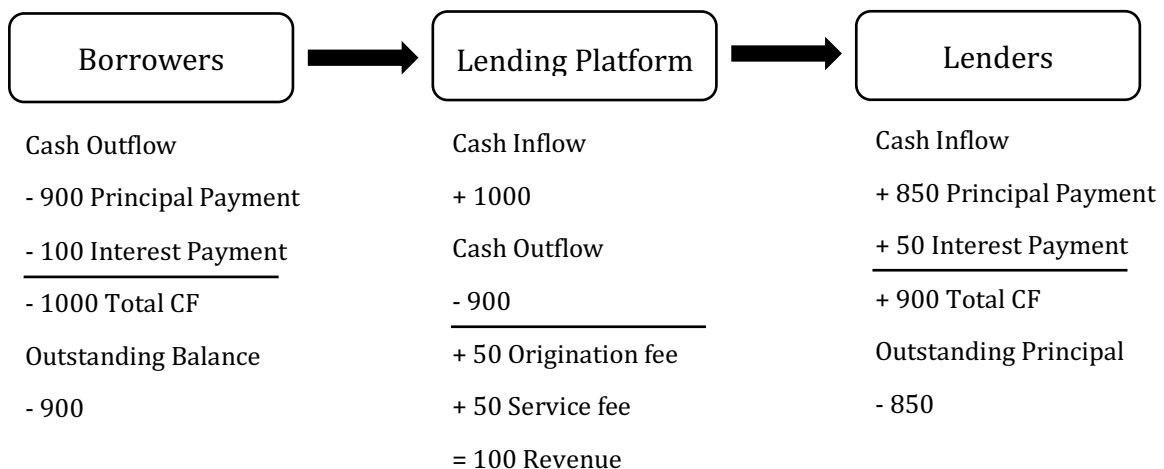
Invested amount (SEK)	Minimum Number of Loans
10,000 – 49,999	40
49,999 – 99,999	50
100,000 – 999,999	60
> 1,000,000	125

Source: [REDACTED]

Additionally, the investor has to choose if they want to invest with a long- or short-time horizon. According to the Lending Platform's website, Autoinvest with a long-time horizon will invest in loans with a maximum time to maturity of 15 years. Investors choosing the short horizon will instead end up with a portfolio of loans with a maximum of 5 years to maturity. All loans in the portfolio will be what the platform refers to as floating rate annuity loans with monthly payments, as this is how all loans on this particular platform are structured. This structure implies that the investor will receive equally sized monthly payments consisting of principal and interest, given that none of the borrowers are late with their payment. However, if one or more investors are late with their monthly payment, the platform has a Credit Loss Fund that immediately reimburses the principal part but not the interest part of the monthly payment.

As the purpose of this paper is to investigate the return to lenders, it is important to understand how the interest rate and annuity payments of a borrower turns into return earned by the investor. Hence, we provide the following simplified example to show what effect the origination and service fee have on the return to the investor², compared to the interest rate the borrower faces. See figure 1.

Figure 1. Operating Model



² Please note that the terms lender and investor are used interchangeably throughout this paper.

If as in the above example the borrower pays their monthly payment consisting of 1000 SEK, the payment reduces both the outstanding balance toward the investor as well as the amount outstanding to the Lending Platform. The latter consists of the origination fee which is paid off proportionally to the principal amount belonging to the lender. Additionally, it pays one twelfth of the stated interest rate on the opening balance. The interest payment can be divided into two parts, the service fee and the return to the lender. Since both parts are calculated based on the outstanding amount the monthly percentage return to the investor can be calculated by subtracting the fee (%) from the interest (%). For instance, say that the yearly interest rates the borrower faces is 12% and the service fee charged by the Lending Platform is 3% on a given loan. In any given month, the borrower will pay $12\%/12=1\%$. When this payment reaches the Lending Platform, they will take out their monthly service fee of $3\%/12 = 0.25\%$ on the outstanding amount. The return in percent that reaches the investor would then be $1\%-0.25\%=0.75\%$ corresponding to an investor Annual Percentage Rate (APR) of $0.75\%*12=9\%$. Hence, the investor APR can easily be calculated through subtracting the annual fee from the annual interest rate the borrower faces. The principal payment can also be divided into two parts, the principal that retires part of the outstanding amount toward the investor as well as a part of the initial origination fee. The first part simply reduces the invested amount for the lender, i.e. the outstanding amount is reduced by this part of the principal payment. The origination fee on the other hand has no obvious connection to the investor. Instead, one can think of the origination fee as a separate outstanding amount that the borrower has toward the Lending Platform. As such, this part of the principal payment reduces the outstanding amount toward the platform and does not affect the lender.

Now, what happens if the borrower fails to pay their monthly payment for some reason? A missed payment will result in no cash flow to the platform. Hence, no fees will be charged from the lender due to the missed payment. Instead, the lender will be reimbursed from the platform's credit loss fund for the principal part of the payment. Therefore, the investor would make a 0% return as the reimbursement covers the principal amount. The credit loss fund covers only the investors choosing to invest through Autoinvest. Even though this represents roughly 90% of the platform's current investors, some still chose to manually decide which loans to invest in. When investing manually, the lender is presented with information regarding the loan, e.g. tenure, interest rate and purpose, as well as information regarding the borrower, e.g. credit score (A-F6), marital status and age. The only two things that differentiates manual investing from automatic investing is that you compose your own portfolio and that you are not covered by the credit loss fund in the event of late payments and defaulted loans. In terms of fee structure, there are no differences.

In an attempt to create liquidity for lenders, the platform has set up their own secondary market. In this market you can sell your entire investment account but not individual loans in that account. However, you can have several investment accounts enabling you to sell parts of your invested capital. The price of the portfolio is set by the selling party as a percentage of the outstanding amount, before it is published on the secondary market where anyone can buy it for your advertised price. However, liquidity remains fairly low and as of May 2019 the number of transactions per month is about 1700 (██████████).

2. Previous Literature

Previous research conducted on P2P lending and its effects has primarily been focused on borrower maximizing factors, while the lenders' perspective has been relatively overlooked. Many platforms, including US market leaders Lending Club (www.lendingclub.com) and Prosper (www.prosper.com), started out with an origination process which included that the lenders bidded on prospective borrowers loans based on both hard verifiable numbers and soft unverifiable information provided in the loan application. As a result, a vast amount of research exists on borrower characteristics and likelihood of funding success (see e.g. Freedman & Jin, 2017) and herding behavior in the bidding process (see e.g. Herzenstein et al., 2011). In a German study by Barasinska (2014) it could be shown that gender has no effect on funding success, despite the opposite being proven among traditional financial intermediaries in the US. As an explanation the author states that gender discrimination seems to be eased by the 'wisdom of the lending crowd' (Barasinska & Schäfer, 2014). Considering that the Lending Platform does not operate in the same way as the above-mentioned platforms, most studies focused on funding success does not contribute much to the context of this study.

As previously mentioned, lender returns have received less attention in the literature but Morse (2015) concludes that at least parts of the cost savings generated by the disintermediation of lending seem to benefit investors. However, she encourages future research on the risk and portfolio selection of lenders to find to what extent these benefits are passed on to investors (Morse, 2015). Hildebrand et al. (2014) compare behavior and outcomes when Prosper removed its origination rewards paid to group leaders, hence affecting their incentives. The key takeaway is that by having a stake in the game, incentives to perform effective and qualitative credit risk assessments is increased (Hildebrand et al., 2014). What is left unresolved however is how intermediaries as whole can be incentivized, rather than just certain group leaders. As mentioned in the introduction, some platforms are implementing hybrid business models to address precisely this issue, but the effects of it are yet to be discovered. Emekter et al. (2015) found that a lower credit grade is associated with a higher hazard rate, and probability of default. Furthermore, they found that the higher interest rates charged on the high-risk borrowers are not enough to compensate lenders for the higher probability of default (Emekter et al., 2015). Loan purpose is also considered to be a factor explaining probability of default, and Serrano et al. (2015) find that e.g. loan consolidation and small business loans are associated with a higher risk of default.

In conclusion, much of the existing literature has been focusing on the behavioral aspects of P2P lending and the borrower side of the exchange. However, limited research on investor returns exists, in which further focus on the investor

perspective is often encouraged. To the best of our knowledge, any research using Swedish P2P lending data is yet to be published. Hence, we aim to combine these two gaps in the existing literature by using Swedish data to examine investor returns.

2.1. Return: Calculation Methodologies

There are multiple techniques for calculating both expected and realized returns. Simply put, the return is the difference between what we invest and what we get back. In reality however it gets more complicated than that, especially when taking risk, multi-period returns and the time value of money into account. Broadly speaking there are three main methods for calculating investment performance results: the basic, time-weighted and money-weighted rate of return. The basic method, often referred to as return on investment (ROI), is easy to interpret but has several limitations. To calculate the ROI, you simply divide the return by the cost of the investment, giving the percentage change over a set period. There is an obvious risk in evaluating long-term performance with this measure as it does not take the time value of money into consideration. Time-weighted return calculations are mostly used to measure the performance of portfolio managers (Fabozzi, 2011) and will hence not be discussed further in this section. For the purpose of this study, the money-weighted rate of return will provide the most accurate measure of return since it accounts for the value of cash flows in all given periods. The money-weighted rate of return is commonly referred to as the internal rate of return. The IRR method was introduced by Dean (1962) and became rapidly accepted among decision-makers, although also criticized from the very beginning. In a study from 1980, Rapp lists several arguments in favor of using the IRR as an investment profitability measure, emphasizing the simplicity *and* flexibility of the method. In order to understand why the IRR metric has become so widely popular, Souder (1973) found that decision-makers seem to rank models according to the following aspects in decreasing order of importance: realism, flexibility, capability, use and cost. Taking these aspects into consideration, the IRR method is often seen to be a suitable way to measure an investment's rate of return.

2.2. Probability of Default: Survival Analysis

Survival analysis is a branch of statistics for analyzing the expected duration of time until one or more events happen. Historically, this type of analysis has been used mainly in medicine or engineering where the time until an event is frequently analyzed, such as death or machine failure. With the introduction of compliance guidelines in the context of financial services business, survival analysis has become more common as a result of the increasing need for accurate credit risk calculations

(Dirick et al., 2017). Hazard models are a class of models in survival analysis with the feature to account for time, making them dynamic as opposed to the conventional static models often used for predicting defaults. Lane et al. (1986) first introduced the Cox proportional hazard model (D. R. Cox, 1972) in finance literature, highlighting its advantages being (1) the lack of underlying assumptions and (2) the ability to explicitly incorporate the time to failure. They applied the model to the prediction of bank failures and found that it tends to identify bankruptcies prior to the actual failure date. The Cox model was first used in the credit context by Narain (1992) and his work has been followed by several authors, e.g. Banasik (1999) who found that applying the ideas of survival analysis give meaningful results in credit scoring. In recent years, Cox paper from 1972 has been cited nearly 1,000 times a year in scientific literature (Allison, 2014). Hazard models often perform better than static models when forecasting default (Dirick et al., 2017) and the Cox regression is the best all-round method for estimating regression models for event history data by the judgement of many. Bellotti and Crook (2009) compared the logistic regression directly with the Cox proportional hazards model and found that the Cox model delivered superior results compared to the logistic regression model, and that the addition of macroeconomic variables further improved the predictions. Baesens et al. (2005) instead compared the Cox model with a neural network survival analysis model, mostly used in the artificial intelligence (AI) context, and found that it did not significantly outperform the proportional hazards model despite its rather complex nature. For further discussion of the advantages and the use of the model, see Cox and Oakes (2018).

2.3. Other Risks Associated with P2P Investing

An area within P2P lending that seems to be more or less unexplored is how to adjust the required return for the liquidity risk that is inherent in the asset class, due to the nature of the operating model of most P2P platforms. Research on illiquidity premiums originates from Amihud and Mendelson's (1986) paper where the effect on asset pricing is investigated through an analysis of the bid-ask spread as a proxy for illiquidity. They find that the market-observed expected return is an increasing concave function of the spread (Amihud & Mendelson, 1986). Inspired by this research, Chen et al. finds a liquidity premium in the levels and changes of bond yields (Chen et al., 2007). Although the characteristics of P2P loans differs from corporate bonds in many aspects, it is reasonable to assume that investors would require a liquidity premium for investing in P2P loans as well as bonds, especially considering the low number of transactions on the secondary market of i.e. The Lending Platform. Lastly, there has been some discussions regarding platform failure and bankruptcy in recent research. For instance, (Havrylchyk & Verdier, 2018) concludes that P2P lending platforms do not suffer from the risk of

bankruptcy runs like traditional financial intermediaries and that the absence of a government guarantee for deposited funds might reduce the moral hazard of platforms compared to banks. Additionally, Havrylchyk and Verdier (2018) comment on the phenomenon that some governments, e.g. in the United Kingdom, require platforms to set up contracts with third parties to ensure continuation of reimbursements to lenders in the event of bankruptcy and that orderly resolution is much more likely for platforms than traditional banks. On the other hand, Morse (2015) argues that a P2P lending platform experiencing financial distress surely will impact the loan performance, and hence the lender returns negatively. The P2P lending platform we study in this paper have a third-party contract with one of the leading collection and credit solution agencies in the Nordics, which further assures the investors that their monthly payments will be received in the event of insolvency (██████████). Finally, it should not be forgotten that investing in P2P loans is associated with traditional financial risks such as volatility, market risk and legal risk (Namvar, 2014).

3. Data

Our empirical analysis of the attractiveness of P2P lending is based on a dataset containing 77,887 monthly records reported between 2015-09 and 2019-04, from a random sample of 6,218 loans provided by the Lending Platform³. Each record contains borrower and loan characteristics as well as information regarding the monthly payment. Among the variables describing the loan specifics, loan purpose is included where loan consolidation is the most common by far. The complete list of variables including a description is presented in Appendix 1, while an overview of the loan purposes can be found in table 2. Important to note is that a vast majority of the loans have not reached maturity yet and are only in its earliest stages. This give rise to a number of issues when trying to adopt the lenders' perspective, since consistency in cash flows and probability of default are two important determinants when evaluating the attractiveness of investing in P2P loans.

Table 2: Summary by loan purpose

Loan Purpose	N	Ratio (%)	Avg. DA (SEK)	Interest Rate (%)	Defaulted Loans
<i>Business</i>	12	0.19	126,909	8.64	2
<i>Divorce</i>	16	0.26	37,378	8.39	0
<i>Education</i>	62	1.00	48,383	9.24	1
<i>Home electronics</i>	49	0.79	40,498	9.09	1
<i>Home improvement</i>	389	6.26	57,391	9.06	23
<i>Kitchen appliances</i>	155	2.49	41,058	8.27	10
<i>Loan consolidation</i>	3216	51.72	86,677	9.28	132
<i>Marriage</i>	39	0.63	51,538	9.43	5
<i>Move</i>	76	1.22	53,510	8.59	4
<i>NA</i>	54	0.87	63,315	9.08	3
<i>None</i>	6	0.10	82,500	8.57	2
<i>Other</i>	776	12.48	60,484	8.34	54
<i>Personal health</i>	88	1.42	41,500	9.28	3
<i>Real estate</i>	2	0.03	35,000	4.41	0
<i>Renovation</i>	86	1.38	55,221	9.39	2
<i>Vacation</i>	222	3.57	37,788	9.54	12
<i>Vehicle</i>	970	15.60	61,614	8.86	37
<i>Total (average)</i>	6,218	100.00	(57,692)	(8.68)	291

Notes: Avg. DA represent the average disbursed amount to borrowers and Interest rate represent the average rate stated in the loan terms, i.e. the rate paid by the borrower.

³ We have requested a random sample of loans from the Lending Platform, but as the sampling process is conducted outside of our control there is an inevitable risk of sampling bias.

3.1. Descriptive Statistics

A summary of descriptive statistics is presented in table 3. We find that loan tenures range from 6 to 180 months and disbursed amount from 5,000 to 350,000 SEK. The average loan tenure is a bit over 5.5 years while the average time since origination is less than one year, showing that many loans are in the beginning of their tenure. Furthermore, some loans have been reported past their maturity date as the minimum remaining tenure is negative 27 months. It is also questionable whether someone aged 119 has actually received a loan through the platform, or that someone with a monthly income of 320,000 SEK would be in need of a small, unsecured credit. These types of inconsistencies in the data can be troublesome and cause noise in parts of the analysis.

Table 3: Summary statistics

Variable	Mean	Median	Std. Dev.	Min	Max
<i>Interest rate (%)</i>	9.06	8.75	3.43	1.95	17.48
<i>Disbursed amount (SEK)</i>	72,382	54,000	52,667	5,000	350,000
<i>Origination fee (SEK)</i>	800.15	495.00	1,375.19	0.00	15,000.00
<i>Outstanding amount (SEK)</i>	72,102	51,500	49,335	0.00	289,011
<i>Loan tenure (months)</i>	66.18	60.00	38.66	6.00	180.00
<i>Time since origination (months)</i>	11.53	9.00	8.23	0.00	43.00
<i>Remaining tenure (months)</i>	54.36	45.00	40.16	-27.00	179.00
<i>Age</i>	42.44	40.00	14.18	20.00	119.00
<i>Monthly income* (SEK)</i>	29,676	27,035	11,867	0.00	320,000
<i>UC Score</i>	4.05	1.83	5.18	0.01	24.93
<i>Ever 1 DPD</i>	0.34	0.00	0.48	0.00	1.00
<i>Ever 30DPD</i>	0.09	0.00	0.29	0.00	1.00
<i>Ever 60 DPD</i>	0.06	0.00	0.25	0.00	1.00
<i>N</i>	6,218				

Notes: The statistics are generated from the last record of each loan.

**Monthly income is reported by the borrower and not verified by the Lending Platform.*

In table 4 the distribution of loans separated by loan status is presented. We find that 167 out of the 6,218 loans in our dataset have reached maturity as of 2019-04, and that 291 have experienced default. Additionally, 1702 of the loans have been repaid early. When comparing the distribution of the number of loans to the distribution of the disbursed amount, the ratios indicate that matured loans are generally of smaller amounts than defaulted loans. However, this can partially be explained by the fact that the loans which have already matured have shorter tenures. Hence, it is likely that they are of smaller amounts.

Table 4: Loan distribution by loan status

Status	N	Ratio N (%)	Disbursed Amount	Ratio DA (%)	Outstanding Amount
Current	•	•	•	•	•
Matured	•	•	•	•	•
Early repayment	•	•	•	•	•
Defaulted	•	•	•	•	•
Total					

Notes: Disbursed amount represent the total amount originated and Ratio DA the proportion per status group. Outstanding amount is the total amount outstanding as of 2019-04.

3.2. Construction of Variables and Data Adjustments

Since we aim to adopt a lender's perspective, some adjustments need to be made to the original data set provided by the Lending Platform. To determine the attractiveness of P2P lending, we are interested in the monthly cash flow received by the lender rather than the amount paid by the borrower. Since the reported principal payment includes the amortization of the origination fee, it will be adjusted proportionally in accordance with equation 1.

$$Adjusted\ Principal_{i,t} = Principal\ Reported_{i,t} - \left(\frac{Principal\ Reported_{i,t}}{Disbursed\ Amount_i} * Total\ Orig.\ Fee_i \right) \quad (1)$$

The total cash flow to the lender is subsequently calculated as the sum of the interest amount and the adjusted principal amount. However, in the very first month the funds are disbursed to the borrower, as such it represents a negative cash flow from the perspective of an investor:

$$\begin{aligned} Cash\ Flow_{i,t} &= Adjusted\ Principal_{i,t} + Interest\ Payment_{i,t} \\ Cash\ Flow_{i,0} &= - Disbursed\ Amount_i \end{aligned} \quad (2)$$

where the *Interest Payment*_{*i,t*} in our data excludes the Lending Platform's service fee. As such the amount in its entirety is a cash flow received by the investor. In addition to generating these variables, a number of observations have to be removed for certain parts of the analysis. This is a result of inconsistencies in the data. For instance, some loans have a double-booked last payment, generating returns far beyond what is possible in reality. Such observations are believed to be data errors and have been removed where they cause noise in the analysis. We contemplated constructing a debt-to-income variable for each loan, as this has previously been shown to have an impact on the probability of default (see e.g. Serrano-Cinca et al., 2015). However, as the income data is both inconsistent and self-reported, we decided to refrain from using the variable.

4. Methodology

While there exist several different methodologies to calculate returns, there seems to be no industry standard for measuring returns on P2P lending platforms. The industry leader Lending Club uses a method they refer to as *net annualized return* (NAR). NAR is an annualized measure of the rate of return on the principal invested over the life of an investment, meaning that as defaults occur over time the NAR will decrease⁴. It is based on actual borrower payments received each month, net of service fees, actual charge offs, and recoveries (Lending Club, 2019). For the purpose of this study we use 1) a simplified method for estimating the theoretical expected return and 2) the IRR method for realized returns, both with a similar approach as Lending Club in regard to service fees and charge offs⁵. Additionally, we introduce survival analysis by fitting a Cox proportional hazard model to our data in order to gain a better understanding of PDs and the factors contributing to default. In this study, we have defined default as when a borrower is 90 days past due date, in line with the standards proposed by the European Banking Authority (2016). If the loan is already written off by the Lending Platform, without having been 90 days past due, it is also considered to be in default. However, loans which have recovered from being 90 days past due and fulfilled their obligations are not considered as defaulted. In the following subsections we outline the methodology behind our return calculations as well how we apply the Cox proportional hazard model with respect to loan defaults.

4.1. Benchmark Return Calculation

Average realized returns are often used as a proxy for expected returns, although the accuracy of this approach is often debated (see e.g. Elton, 1999). However, we will use historical data to construct a benchmark to use as a point of reference for expected returns. The benchmark expected return will be constructed using the average interest rates as well as the service fee spread presented on the Lending Platform's website. The rate of return for a successful, non-defaulting, loan would be the monthly interest rate faced by the borrower minus the monthly fee charged by the Lending Platform, as they are both calculated based on the outstanding amount.

⁴ For a complete explanation of the NAR method, please see the Lending Club website (Lending Club,).

⁵ Note: All return estimates and measures presented throughout this paper is on a before tax basis. Current tax regulation as of May 2019 consists of 1) 30% tax on interest received 2) 30% tax on realized capital gains 3) 70% of realized capital losses are deductible.

4.2. Internal Rate of Return

The internal rate of return takes the time-value of money into account and is defined as the discount rate at which the net present value (NPV) of the cash flows generated from the investment is equal to zero (Berk & DeMarzo, 2017). Even though there is no industry standard for calculating return on P2P platforms, the IRR is a common measure among investors in many fields, as pointed out in the literature section. A simple rule is to accept the investment if the IRR is greater than the expected or required return and reject the investment if the IRR is less than that. However, it should be noted that the IRR has several disadvantages such as the risk of giving multiple IRRs if the cash flows change sign more than once or giving opposite recommendations as the NPV rule⁶ in case of upfront cash inflows (Berk & DeMarzo, 2017). In the context of P2P lending, the investor's initial cash flow is negative, and the following payments are fixed. Hence, there are no sign changes in the cash flows other than in the beginning, which further favors the use of the IRR for calculating returns. One of the assumptions when using the IRR is that any intermediate cash flows are reinvested at the discount rate, although also widely debated whether this actually holds true or not (see e.g. Rapp, 1980 or Rich & Rose, 2014). However, as the IRR is used in our context, it represents the average annual rate of return without the effect of compounding. Hence, it is comparable to the yearly interest rate the borrower faces, reduced by the service fee charged by the Lending Platform. The IRR is calculated through solving the following equation:

$$0 = NPV = \sum_{n=0}^N \frac{CF_n}{(1 + IRR)^n} \quad (3)$$

where CF_0 is the initial investment, CF_n the monthly cash flows, n the number of periods and N the loan tenure.

We apply the IRR method of calculating lender return on three subsets of loans. The first subset of loans are those that have reached maturity and been fully paid off. As for the second subset, it consists of loans that have been repaid in full before reaching maturity. Finally, the third subset include all loans that are considered to be defaulted. For every subset, the IRR of each individual loan is calculated before it is aggregated on a credit score level to enable comparisons across credit scores as well as against the benchmark return.

Since the purpose of this paper is not to study portfolio theory or optimization, we have not used any sophisticated techniques for constructing portfolios out of the subsets of loans described above. However, as we would still like to present a point

⁶ The NPV decision rule specifies that all independent projects with a positive NPV should be accepted.

of reference for what the average expected return of an Autoinvest portfolio might look like, we have implemented a simplified approximation. Expected return is generally calculated using the equation below (Bodie et al., 2014):

$$E(r) = \sum_s (p_s * r_s) \quad (4)$$

where p_s is the probability of scenario s and r is the return in that scenario. There exist countless scenarios from investing in most assets, including P2P loans. However, very simplified one could think of two main scenarios, either the borrower pays their principal and interest, or they default after which the investor receives nothing⁷. The equation would then read:

$$E(r) = p_d * r_d + (1 - p_d) * r_r \quad (5)$$

where p_d is the probability of default, r_d is the return if in the event of default and r_r the return if the loan is repaid. Traditional financial institutions that lend money have to estimate credit loss according to the Basel II framework, a calculation that generally relies on three important parameters; 1) Exposure at Default (EAD) 2) Loss Given Default (LGD) and 3) Probability of Default (PD) (BIS, 2005). The latter explains the probability of default in a given portfolio and can be proxied using different techniques. EAD on the other hand is an estimation of the outstanding amount at risk in the event of default. Finally, the LGD describes in percent how much of the amount at risk that is estimated to be lost in the event of default. While this method is the industry standard for estimating expected credit losses, it is not easily transferred to the P2P lending data we are using for two main reasons. Firstly, we are calculating percentage returns and not amounts, which is what the EAD is mainly used for. Secondly, the interest rate is used in the event of no default, which implies that the downside in event of default should be comparable to this measure, i.e. the percentage lost adjusted for received interest. As we would like to avoid the use of complicated estimation techniques described by the Basel II framework, for the reasons listed above, we have to find an alternative way to estimate these parameters. The IRR can be calculated for loans that are defaulted and subsequently used as the return in the scenario of default. In the scenario of no default, we will use the IRR of matured loans as a proxy for the return. This is presented below in equation 6:

$$r_{d,i} = IRR_{d,i}, r_{m,i} = IRR_{m,i} \quad (6)$$

The IRR of defaulted loans will take into account the amount lost when default occurs, i.e. include both of the parameters EAD and LGD as described above. The estimation of the portfolio return will be done with two different assumptions

⁷ Note: As of today, the investor would be reimbursed by the credit loss fund. As mentioned previously, this is not a guarantee and might not be something investors can count on in times of worse economic conditions.

regarding the credit loss fund, either the fund does not cover any of the future cash flows *or* it covers all of the principal payments. In the former, each credit score will be treated as having two scenarios as described earlier on, either a borrower fulfils their obligations and pays the full principal and interest until maturity, in which case the average IRR from the subset of matured loans will be used as the return. Or, the borrower defaults at some point in time, and for this scenario the average IRR of the defaulted loans in that credit score will be used. When full reimbursement is considered, the return is assumed to be 0% in the default scenario.

$$E(r_p) = \sum_{c=A}^F w_c * E(r_c) \quad (7)$$

In line with equation 7, the sum of all weighted returns will represent an approximation of the return expected of an Autoinvest portfolio. The approximation will be more accurate for an Autoinvest portfolio with a short time horizon, as the average IRRs used will be calculated on loans that have maturities below 5 years.⁸

For this approximation the probability of default, p_d , will be estimated as the percentage of the initial investment that defaults, as described in equation 8.

$$p_{d,c} = \frac{\sum_1^d \text{Disbursed Amount}_d}{\sum_1^i \text{Disbursed Amount}_i} \quad (8)$$

where c denotes the credit risk class, d denotes the d :th defaulted loan and i the total number of loans. We expect this estimation of PD to be lower than the actual long run default rates, as many of the loans in the data set have only existed for a small fraction of their total duration. Hence, our next step will be to further investigate the default probabilities.

4.3. Survival Analysis: The Cox Proportional Hazard Model

The purpose of introducing survival analysis in this study is to gain a better understanding of the factors affecting the likelihood of default for borrowers on the Lending Platform, as defaults are a main contributing factor to the return realized by investors. Most models for failure prediction apply probit or logit techniques to determine the probability of default⁹. The Cox proportional hazard model takes this approach a step further as it allows predicting not only the probability of default, but also the estimated time of this event (Allison, 2014). The predictions are quite limited however as the model cannot predict what happens after the last observed

⁸ In the data set none of the matured loans have maturities over 5 years.

⁹ Probit and logit models are parametric models where the dependent variable is a binary response, commonly used to predict future events. For further information see e.g. (Aldrich & Nelson, 2006).

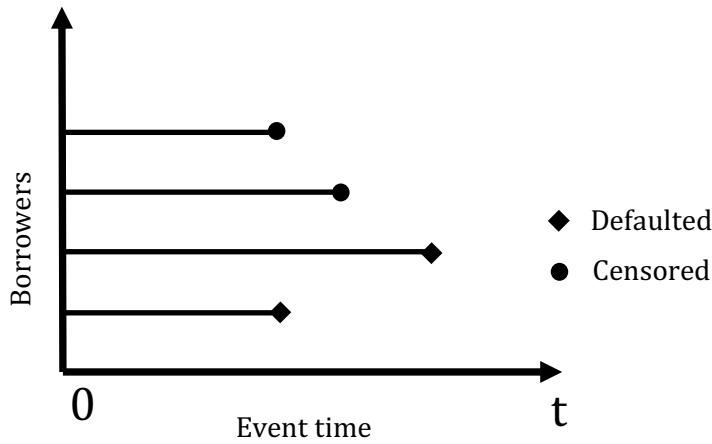
time of event in the sample, but it avoids the risk of extrapolation, i.e. assuming that any existing trend will continue. In a Cox regression model, the dependent variable is expressed as a *hazard*. The model describes the relation between the occurrence of an event and a set of independent variables, usually called covariates. The hazard in this context is the probability that a loan default. It is assumed that the hazards stay constant over time, why it is referred to as a proportional model (Koletsi & Pandis, 2017). To test the assumption of proportional hazard we utilize a Schoenfeld residual test (Schoenfeld, 1982). The Schoenfeld residual is calculated for each observation that has a default event and for each individual explanatory variable. If the hazards are in fact proportional, the residuals should be uncorrelated with time. The Cox model also allows for the inclusion of time-varying covariates, i.e. covariates with the ability to change over time. In such cases, the complexity of the model increases significantly, why the inclusion of e.g. macroeconomic variables in the modelling is considered to be outside the scope of this paper.

One of the main benefits with the Cox model is that it is particularly suitable for event data with large amounts of observations, and only a small fraction of events occurring. For P2P lending data, the number of periods in which borrowers *do not* default composes the vast majority of data points rather than the opposite. The Cox model allows for censoring of these observations for which the event never happened; a process further explained in the following section. While the small fraction of events is not causing any problems, time to maturity and the fact that most loans are only in its earliest stages are, especially since we cannot tell what happens after the last observed event. To address this issue, the time variable could be expressed as a *proportion of time*, defining the fraction that is left of the loan duration. While this would be interesting and perhaps provide a more accurate estimate of survival times during the full period of a loan, we have not been able to find any existing literature supporting this approach.

4.3.1. Observation Censoring

In survival analysis, a certain proportion of the cases is censored. Censoring occurs when the event of interest has not yet been observed at the moment of data gathering. At this point in time our data set is heavily right censored, meaning that for the vast majority of the observations, the event of interest has not yet occurred. An event is the pre-specified endpoint of the study, for instance death or disease recurrence. In the context of credit risk, the event of interest is borrower default. When applying survival analysis to model time to default, as in the case of this study, all cases not having experienced default until the time of data gathering are censored at the last time recorded. By incorporating these non-event observations, the statistical power of the model is significantly increased.

Figure 2. The Censoring Process



4.3.2. Variable Selection

The Cox regression investigates the association between time to default and one or more predictor variables. Since we are performing the analysis without time-varying covariates, only variables that are constant over time are available for selection. For each loan purpose, living status and marital status a dummy variable is created, resulting in a total of 30 dummy variables. A complete list of the variables is presented in Appendix 1, however using variables related to transaction data is not possible since we are not including time varying covariates in our model. Fitting the model on all relevant combinations of variables would require a significant amount of time, why an iterative stepwise regression is applied instead. Stepwise regression means that variables are added and tested successively, and then dropped if not proving statistical significance. Although stepwise regression as a method for variable selection has received some criticism, it is still valuable as a way of identifying covariates that are likely to have an impact on the dependent variable (Frey, 2018). We apply a threshold on the p-value of 0.2 to find variables that might have an impact on the probability of default. The resulting variables is then used in the final model.

4.3.3. The Choice of Origin for the Measurement of Time

One aspect of model choice is the question of when time begins. This question is relevant to both parametric and semiparametric regression models, but the proportional hazards model offers a wider range of possibilities. The date of issue is a natural starting point for calculating time of default, but even in this seemingly straightforward example there is room for disagreement. In formulating this hazard model, one could let the hazard be a function of a person's age or calendar time rather than time since the issuance of the loan. However, in the case of credit default

the hazard is expected to depend on time since origination, at least to some extent. The hazard could also be thought to depend strongly macroeconomic factors and vary with historical conditions, that affect all borrowers in the same way, meaning that calendar time would be an appropriate time scale. In the end, we have chosen to use time since origination mainly for two reasons. As mentioned in the previous section, the inclusion of external time-varying covariates is outside the scope of this analysis. Secondly, the time period of our sample ranges only from 2015-09 to 2019-04, meaning that no major event of interest has taken place during this period. By event of interest one could think of a financial crisis, unusual GDP growth or any macroeconomic factor having an impact on the household economy.

Important to note in the context of time is that with discrete time data, as in this study, there is a risk that two or more loans experience default at the same recorded time. This would cause something called a tie, creating a problem since the Cox model takes time as continuous and uses ranks of event times to fit the model. There are multiple ways to handle this issue, and we have chosen to use the Efron approximation method (Efron, 1977) since it is often considered to be the best choice (see e.g. Borucka, 2014 or Allison, 2014). This method requires only slightly more computational power than e.g. the Breslow method¹⁰ while yielding a better approximation.

¹⁰ The Breslow Method is an alternative approach to handling ties in the data when using the Cox model.

5. Empirical Results

In the following section the results from the method outlined in section 4 will be presented. First, we will present the results from the return measures, after which the results from the survival analysis and its implications on default probabilities will be presented.

5.1. Benchmark and Internal Rate of Return

The average interest rate per credit score ranged from 4.56% to 13.83% with an overall average interest rate of 9.05%. After deducting the service fee spread, we arrive at an interval in which one would expect the IRR to lie between for all non-defaulted loans. Both the minimum and maximum return is increasing when moving toward lower credit scores, which is expected as these return figures are *unadjusted* for expected credit losses as well as the time value of cash flows. The expected credit losses are likely to be higher in the lower credit scores, an assumption which is also supported by the percentage of defaulted loans in each credit score. The results are presented in table 5.

Table 5: Benchmark return

Credit Score	N	Interest Rate (%)	Fee Spread (%)	Min Return (%)	Max Return (%)	Defaulted Loans
<i>A (highest)</i>	658	4.56	1.50-3.27	1.29	3.06	•
<i>B</i>	852	5.93	2.63-3.75	2.17	3.29	•
<i>C</i>	896	7.03	3.45-4.20	2.83	3.58	•
<i>D</i>	1334	8.96	3.15-4.50	4.46	5.81	•
<i>E</i>	1281	10.51	3.70-5.50	5.01	6.81	•
<i>F (lowest)</i>	1197	13.83	4.45-5.50	8.32	9.37	•
<i>Total (average)</i>	6,218	(9.05)	NA	NA	NA	•

Notes: Interest rate is the average rate charged from the borrowers in each risk class. Fees represent the fee charged by the Lending Platform, retrieved from their website.

In table 6 the results from calculating the IRR on the three subsets of loans is presented. Since the loans in Panel A have reimbursed investors both for the principal as well as interest throughout the tenure, all of the loans have a positive IRR. Interestingly, all credit scores have maximum IRR that is above the benchmark expected return, indicating that the investors on average would have been reimbursed for more than the interest minus service fee. Alternatively, the Lending Platform have historically charged lower fees than those presented on their website today. Unfortunately, we have no information regarding historical fees. It should be noted that each credit score contains a low number of observations, why we refrain from drawing any substantial inferences.

In the second subset of early repaid loans the average IRR for each credit score is comparable to the ones of matured loans, with only minor discrepancies. For all credit scores but F the average IRR is higher for early repaid loans than for the ones that are matured. A likely reason for this is that if a loan is retired early there is less chance of a loan being late with payments which results in a higher return as the time value of money is an important determinant of IRR. As can be read from the table, each credit score has a minimum IRR of 0%, indicating that the borrower has immediately repaid the loan before any interest is accrued. Whether or not this is realistic can be debated, however it is not uncommon to refinance your loans as seen from the fact that a majority of the loans have the purpose of consolidating or refinancing other loans.

The IRRs of defaulted loans¹¹ were expected to be very negative as the majority of loans in the data are far from matured, as presented in section 3. The a priori belief of the IRR for different risk classes in this subset is arguable. On one hand, loans with a good credit score is believed to have a lower probability of default and possibly default later on in the loan, if at all. On the other hand, a low credit score would be connected with a higher interest rate, meaning that lenders would have received higher cash flows when default occurs, *ceteris paribus*. Considering that the number of defaulted loans is only at 291 and that many loans have not even reached halfway through to maturity, the timing of default becomes even more important relative to the interest rate. Furthermore, the minimum IRR for each credit score sits at -100%. Even though this indicates that the borrowers have defaulted as early as in the first month, causing the investor to lose all invested money, other factors could yield an IRR extremely close to -100%. This is because the IRR generates a yearly return. Implying, that a borrower defaulting less than a year into the loan, with 80% left to pay until the cash flow equals the invested amount will have an IRR lower than -80%.

¹¹ The definition of default as presented in section 4 is 90 days delinquent or written off by the Lending Platform.

Table 6: IRR and maximum benchmark return

Credit Score	N	Mean	Median	Std. Dev.	Min	Max	Interest Rate	Max Return
Panel A: Matured loans								
A	34	2.54	2.46	0.85	1.31	3.76	3.38	1.88
B	37	2.78	2.59	1.12	1.45	4.53	4.15	1.52
C	28	3.37	2.69	1.51	1.42	7.57	4.99	1.54
D	25	5.07	4.52	1.06	3.95	7.84	6.67	3.52
E	21	6.42	6.24	0.80	5.18	8.02	8.02	4.32
F	4	9.54	9.21	1.18	8.60	11.14	11.32	6.87
Panel B: Early repaid loans								
A	139	2.62	2.57	1.06	0.00	5.54	4.02	2.52
B	199	3.02	3.15	1.37	0.00	6.67	5.11	2.48
C	236	3.68	3.40	1.93	0.00	8.87	6.40	2.95
D	294	5.19	5.14	1.87	0.00	9.52	8.11	4.96
E	264	6.69	6.73	2.19	-0.11	11.91	9.76	6.07
F	193	8.97	9.23	3.06	0.00	15.73	13.36	8.91
Panel C: Defaulted loans								
A	•	•	•	•	•	•	•	•
B	•	•	•	•	•	•	•	•
C	•	•	•	•	•	•	•	•
D	•	•	•	•	•	•	•	•
E	•	•	•	•	•	•	•	•
F	•	•	•	•	•	•	•	•

Notes: Interest rate represent the rate charged from the borrower and max return represent the maximum theoretical benchmark return.

When looking at the average interest rates across the three different subsets an interesting pattern is revealed. For each credit score, the lowest interest rate appears in the matured section, the second lowest in the early repaid section and the highest in the defaulted section. Finding the highest rates in the subset of defaulted loans is not surprising though, as high interest rates are one way of compensating lenders for a higher probability of default. That the average interest rate is higher for all credit scores in the subset of early repaid loans can be due to several reasons. Although the causality is unknown, it is imaginable that these borrowers repay their loans as a result of finding lower interest rates elsewhere.

Our point of reference for the return of an Autoinvest portfolio, using the IRRs above as the measure of return, is presented in table 7. Column 6 describes what each credit score contributes to the portfolios overall return, adjusted for default, when we assume that the credit loss fund does not reimburse principal payments. The total expected return of the portfolio is then only 0.43%. However, when we assume reimbursed principal payments the return of the portfolio jumps to a much higher level of 4.95%. Even though the discrepancy between these two figures are very

large, it is not surprising that the effect of not having to bear any principal losses is large.

Table 7: Autoinvest portfolio estimate

Credit Score	PD (%)	IRR (%)	Default IRR (%)	Weights (%)	Wt. Return w/o CLF (%)	Wt. Return w CLF (%)
A	0.80	2.54	-90.01	0.10	0.18	0.25
B	3.07	2.76	-71.62	0.15	0.07	0.40
C	4.51	3.37	-68.26	0.15	0.02	0.48
D	5.92	5.07	-77.57	0.21	0.04	1.00
E	9.26	6.42	-75.99	0.21	-0.25	1.22
F	7.96	9.54	-84.10	0.18	0.38	1.58
Portfolio					0.43	4.95

Notes: PD is the probability of default, IRR is the return for non-defaulting loans and default IRR represent the negative return in the case of default. Wt. return w and w/o CLF describes what each credit score contributes with to the portfolios overall return, adjusted for default. Weights approximately represent the overall distribution of loans, i.e. the average Autoinvest portfolio.

5.2. Default: Survival Analysis

In the following sections, we present the results from the survival analysis. First, we present the results of the variable selection after which we present and discuss the regression output. Finally, we present results related to the prediction of default.

5.2.1. Variable Selection

The stepwise regression used to identify variables which have significant impact on the hazard rate resulted in an output of 13 variables. When calculating the variance inflation factor (VIF), the algorithm suggested that our initial model suffered from multicollinearity. If problems with multicollinearity occur, as in this case, it can be resolved through the use of a threshold for the VIF. However, Hair et al. (2014) suggests that a VIF below 10 indicates that it is not severe enough to warrant correction of the model. As such, all variables initially suggested was kept in the model, which is presented in table 8.

5.2.2. Cox Regression Result

The aim when fitting a Cox model to time-to-event data, such as the loan data in this study, is to estimate the effect of covariates on the baseline hazard function. The baseline cumulative hazard can be used to calculate the survival probability $S(t)$ for any borrower at time t , taking its covariate profile¹² into account. The hazard function $h(t)$ is the conditional probability of defaulting at time t having survived to that time. The *Coefficient* reported in table 8 relates to the hazard, with a positive

¹² Covariate profile represent the specific values for each variable of an individual borrower.

sign indicating a higher likelihood of default. In line with our expectations, the *Credit score* covariate has a negative sign and hence a positive impact on survival. The credit score is assigned by the Lending Platform and a higher score indicates higher creditworthiness. The *Hazard rate* is the exponentiated coefficient, which is interpreted such that, everything else equal, a one-unit change in *Interest rate* is associated with a 11.6% increase in the hazard rate. A one-unit change in *Credit score* towards the better is however associated with a 13.9% (1-0.861) lower hazard rate, a direction in line with our prior beliefs. Regarding loan purposes, we expected loan consolidation to have a negative impact on survival in line with the study of Serrano-Cinca et al. (2015). This turned out not to be the case in our sample, which could potentially be explained by different behavioral patterns of UK and Swedish borrowers. To test the assumption of proportionality, the Schoenfeld residual was calculated for each default observation as described in section 4. If the hazards are in fact proportional, the residuals should be uncorrelated with time. Four of our explanatory variables, namely *age*, *marital status single*, *marital status divorced* and *loan purpose none*, seem to be correlated with time as they generate significant p-values. However, as noted by Allison (2014) the proportional hazard assumption is often a satisfactory approximation even when violated.

Table 8: Cox regression output

Covariates:	Coefficient	Hazard Ratio	SE(Coef)
<i>Interest rate</i>	0.110 ***	1.116	0.032
<i>Credit score</i>	-0.149 *	0.861	0.077
<i>Age</i>	-0.012 **	0.988	0.005
<i>Loan tenure</i>	0.003 *	1.003	0.002
<i>Marital status: Single</i>	0.375 ***	1.455	0.123
<i>Marital status: Divorced</i>	0.808 ***	2.244	0.266
<i>Purpose: Loan Consolidation</i>	-0.414 ***	0.661	0.133
<i>Purpose: Vehicle</i>	-0.425 **	0.654	0.194
<i>Purpose: Marriage</i>	0.874 *	2.396	0.460
<i>Purpose: Education</i>	-1.110	0.329	1.006
<i>Purpose: Kitchen appliances</i>	0.473	1.605	0.335
<i>Purpose: None</i>	1.193 *	3.296	0.717
<i>Living status: Apartment owner</i>	-0.455 **	0.635	0.187

N Total = 6178 Event = 291

Notes: A positive sign of the coefficient indicates a higher probability of default.

Significance codes: 0.01 '***' 0.05 '**' 0.1 '*'

5.2.3. Predictions Based on the Cox Model

Table 9 displays the cumulative survival function *at mean* of all covariates in the model. The survival function has a row for every observed time for default, from 3 to 31, in terms of months since origination. The numbers in the *Cumulative survival* column are the estimated probabilities of “surviving” to each point in time without

defaulting. The survival function can be derived from hazard function and vice versa. For example, the probability of a loan making it to month 12 without experiencing default is estimated to be 0.960 with a 95% confidence interval ranging from 0.954 to 0.967. Using this table, we can for example estimate the probability of default during the second year of the loan tenure, given that the loan has not defaulted after the first year, i.e. in month 12. This probability of defaulting between month 13 and 24 after origination is calculated as $(0.957-0.883)/0.957 = 0.077$, indicating a baseline probability of default at 7.7%. Note that this is a baseline probability, for any individual borrower the likelihood of default will be affected by the profile of its explanatory variables.

Table 9: Cumulative survival function

Number of Observations:			Total 6218	Event 291
Time	Number at Risk	Number of Events	Cumulative Survival	SE
5	4827	19	0.990	0.0013
10	2988	14	0.971	0.0026
12	2416	11	0.960	0.0034
13	2118	8	0.957	0.0036
24	500	3	0.883	0.0098
26	372	3	0.868	0.0115
30	174	1	0.846	0.0152
31	141	1	0.838	0.0172

Notes: The complete table with all rows from 3-31 is found in Appendix 2.

Time is number of months since origination. Number at risk represent all borrowers still at risk in the sample and number of events equals number of defaults each period.

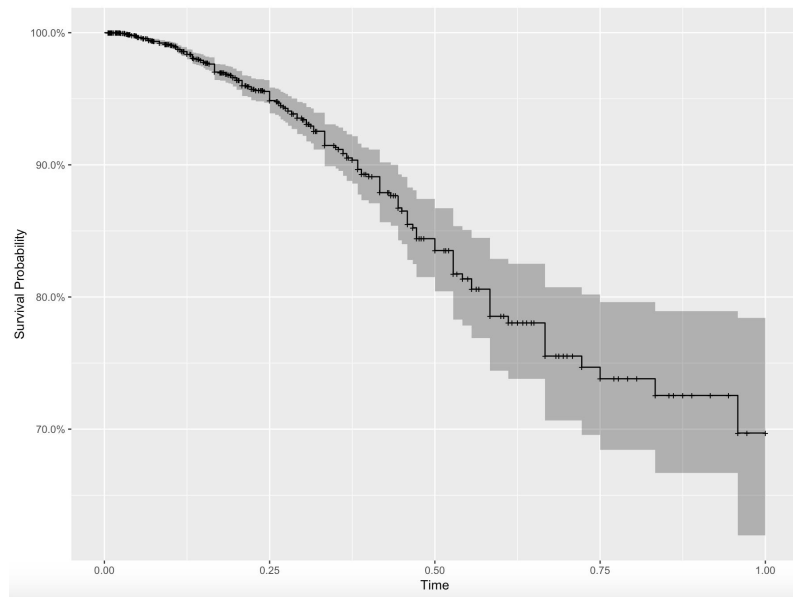
Cumulative survival is the estimated probability of surviving to each time point, with the standard error presented in column 5.

The survival function presented in table 9 stops at month 31, the last observed time of default. As such, we cannot tell what the function looks like after that. This causes a problem when trying to estimate probability of default over the lifetime of some loans, considering that they can range up to 180 months. To address this problem, we modified the dependent time variable to be expressed as a proportion of time¹³, rather than actual months since origination. As mentioned in section 4 however, no literature either supporting or speaking against this approach seem to exist, why these results should be taken with caution. With the modified time variable, the estimated probability of survival until the end of the loan tenure would be somewhere around 70%. The last observed time of default occurs at $t = 0.958$,

¹³ The proportional time variable is calculated as number of months since origination divided by total loan tenure. Hence, all records take on a number between 0 and 1.

meaning that it defaulted near the very end of the loan tenure. Figure 3 displays the survival curve at mean of all covariates in the model. The instantaneous rate of event¹³, i.e. the rate of defaulting at any time t , is the slope at that time point of the survival curve.

Figure 3: Survival curve at mean of all covariates with the time variable expressed as a proportion of time.



¹³ The instantaneous rate of event is calculated as: $(S(t) - S(t + dt)) / dt$, where $S(t)$ is the proportion not defaulting at time t .

6. Conclusion

In this section we will present the conclusions and implications from our empirical analysis. In addition, we will provide a few suggestions for further research related to P2P lending.

6.1. Concluding Thoughts

Throughout this paper we have been concerned with how to measure returns as well as the effect on returns of borrowers defaulting on their obligations. Firstly, for each credit score we constructed a benchmark return unadjusted for default which, in line with our expectations, indicated that the lower the credit score the higher the return. Subsequently, we calculated the IRR of the loans for which we had a complete set of cash flows. In many of the cases, the average IRR was higher than the maximum benchmark return. Although this was a surprising result, there are several potential explanations for this disparity. We believe that the most likely reason is that the Lending Platform have adjusted their fee structure and that our estimated maximum benchmark return is too low. Another explanation, yet not as likely, is that our interest payment data is in fact not excluding service fees. However, this seems doubtful as it has been clearly specified as the amount without fees. Additionally, when manually inspecting a few loans in the data it is evident that monthly payments are lower than what the borrower's interest rate suggests. The IRR of defaulted loans were found to lie on average around -78%, indicating that when a borrower defaults the investor loses a significant amount of money. Furthermore, two points of reference regarding the return of an Autoinvest portfolio were introduced. On one hand, we considered a case where the platform's credit loss fund is non-existent, resulting in an overall estimate of 0.43% yearly return in the portfolio. On the other hand, we allowed for the credit loss fund to cover the entire principal amount, making the investor unable to lose money. The portfolio returns then soared to a level of 4.95% in average yearly return. However, in reality the expected return is bound to lie in between these two figures. This is because the CLF actually covers the principal amount as of today but is unlikely to be able to reimburse investors fully in times of poor macroeconomic conditions and financial distress. Whether or not the true expected return is enough to compensate investors for additional risk beside default is left uncommented. This is mainly because the data used for our analysis is not enough to give a representative view of the long run performance of investing in P2P loans on the platform and even more uncertain when considering the entire Swedish or European market. As a final remark on the expected returns, we noted that the estimation of PD used when constructing the default adjusted return of an Autoinvest portfolio is unlikely to be an ideal representation of the long run probability of default. Hence, we introduced survival

analysis to facilitate further examination of significant factors impacting the hazard of default. Although our data spanned over a time period not sufficient to predict the lifetime probabilities of default, we could still potentially gain an understanding of what might affect the default probability. Consequently, we fitted the Cox proportional hazard model on our data and found that both hard figures such as the interest rate as well as unverifiable information like the purpose of the loan were significant. For instance, the loan purpose consolidation was found to decrease the hazard of default in our model which is in line with some of the previous research (Polena & Regner, 2018). However, another study found contrasting results, i.e. loan consolidation was instead found to be associated with a slight increase of the hazard (Serrano-Cinca et al., 2015). For future reference, results could be improved by two main efforts. Firstly, when data consisting of a higher proportion of matured loans is available both the prediction accuracy and length can be improved significantly. Secondly, when the quantity of data increases one could introduce subsets based on the loan tenure to better capture the probabilities for each length of the loan.

In conclusion, we find that the IRR of repaid loans are generally higher than our benchmark return, indicating that adjustments have been made to the service fees. On the other hand, when adjusting for defaults we find an indication that the weighted annual return of an Autoinvest portfolio should lie between 0.43% to 4.95% depending on the reliability of the platform's credit loss fund. Additionally, we find that the default hazard is impacted by both verifiable and unverifiable information. All in all, we contribute to the existing literature through exploring the investor's perspective of P2P lending as well as by researching using data from a Swedish platform¹⁵. The former being under-represented in the existing literature and the latter being, to the best of our knowledge, previously unseen in the literature.

6.2. Suggestions for Further Research

Lastly, we would like to propose some suggestions for further research of the investor's perspective of P2P lending. In some ways, this paper was limited to the properties of the data obtained. For instance, with very few loans being matured it raises questions regarding the robustness of the results presented. We would like to encourage research which can validate both the return calculations, but even more so the survival analysis used in the P2P lending context. As have been shown in this paper, defaulting loans have an immense impact on the potential for returns. As data availability increases both quantity wise and time horizon wise, we suggest that the

¹⁵ Note: We would like to comment on the risk of funding bias as we are using data provided by the Lending Platform. None of the authors receive any kind of financial compensation for the work presented in this paper, neither are they aware of any other affiliations with the platform, including financial holdings, that may impact the objectivity of what is presented in this paper.

Cox model used in this paper is developed further by incorporating time-varying covariates. This will allow for the use of macroeconomic factors as covariates, meaning that one can potentially see the effect on the default hazard of factors such as GDP-growth, employment and stock market performance. Furthermore, this would allow for predictions and simulation of how investing in P2P loans might be affected by an economic depression. Finally, we also suggest that future research is directed at using modern portfolio theory to investigate the attractiveness of adding Swedish P2P loans to a market portfolio.

7. References

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8. Appendix

8.1. Appendix 1

Appendix 1: Variables and description

Variable Name	Description
A. Loan Characteristics	
<i>Loan ID</i>	Key for identification of each loan
<i>Interest rate</i>	Floating annual interest rate paid by the borrower
<i>Risk class</i>	Grade from A-F assigned to the loan by the Lending Platform
<i>Disbursed amount</i>	Monetary amount paid out to the borrower
<i>Loan tenure</i>	Loan tenure in months
<i>Fee</i>	Monetary origination fee to be paid by the borrower
<i>Origination month</i>	Loan origination month
<i>Loan purpose</i>	Purpose of the loan, categorized by business, divorce, education, home electronics, home improvement, kitchen appliances, loan consolidation, marriage, move, NA, none, other, personal health, real estate, renovation, vacation and vehicle
<i>Reporting month</i>	Record reporting month
<i>Time since origination</i>	Number of months since origination
<i>Remaining tenure</i>	Number of months until maturity
<i>Outstanding amount</i>	Borrowers current outstanding amount (including origination fee)
<i>Principal amount</i>	Monthly principal amount paid by the borrower
<i>Interest payment amount</i>	Monthly interest amount received by the lender
<i>1 day past due</i>	Dummy variable if ever 1 day delinquent
<i>30 days past due</i>	Dummy variable if ever 30 days delinquent
<i>60 days past due</i>	Dummy variable if ever 60 days delinquent
<i>90 days past due</i>	Dummy variable if ever 90 days delinquent
<i>Amount 1 day past due</i>	Outstanding amount when 1 day delinquent
<i>Amount 30 days past due</i>	Outstanding amount when 30 days delinquent
<i>Amount 60 days past due</i>	Outstanding amount when 60 days delinquent
<i>Amount 90 days past due</i>	Outstanding amount when 90 days delinquent
<i>Written off</i>	Dummy variable if loan is written off by the Lending Platform
<i>Amount written off</i>	Outstanding principal amount when written off
<i>Completed loan</i>	Dummy variable if matured or paid off early
B. Borrower Characteristics	
<i>Age</i>	Borrower age at origination date
<i>UC score</i>	Credit score collected from UC
<i>Employment status</i>	Employment status, categorized by employed per hour, job seeker, pensioner, pensioner early, pensioner sick, permanent employee, probation, self-employed and temporary employment
<i>Monthly income</i>	Monthly income, reported by the borrower
<i>Living status</i>	Living status, categorized by apartment owner, house owner, renting, second hand renting, shared living and weekend cottage
<i>Marital status</i>	Marital status, categorized by apart, divorced, married, none, cohabitant, single and widower

Notes: Borrower and loan characteristics are reported once are hence constant over time, payment information is reported monthly.

8.2. Appendix 2

Appendix 2: Cumulative survival function

Number of Observations:			Total 9931	Event 451
Time	Number at Risk	Number of Events	Cumulative Survival	SE
3	5935	16	0.998	0.0004
4	5324	39	0.993	0.0010
5	4827	19	0.990	0.0013
6	4369	17	0.987	0.0015
7	3972	18	0.983	0.0018
8	3602	23	0.978	0.0022
9	3239	10	0.975	0.0024
10	2988	14	0.971	0.0026
11	2729	20	0.964	0.0031
12	2416	11	0.960	0.0034
13	2118	8	0.957	0.0036
14	1903	8	0.953	0.0039
15	1693	13	0.946	0.0045
16	1557	12	0.938	0.0050
17	1410	6	0.934	0.0053
18	1223	5	0.930	0.0056
19	1058	11	0.921	0.0064
20	932	7	0.914	0.0069
21	835	7	0.906	0.0075
22	729	5	0.900	0.0081
23	612	7	0.889	0.0091
24	500	3	0.883	0.0098
25	422	3	0.876	0.0106
26	372	3	0.868	0.0115
27	332	2	0.862	0.0123
28	282	1	0.858	0.0129
29	218	1	0.853	0.0138
30	174	1	0.846	0.0152
31	141	1	0.838	0.0172

Notes: Time is number of months since origination. Number at risk represent all borrowers still at risk in the sample and number of events equals number of defaults each period. Cumulative survival is the estimated probability of surviving to each time point, with the standard error presented in column 5.