An Analysis of The Future of Peer-to-Peer Lending

Is P2P-lending a relevant asset class for investors?

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Abstract

Peer-to-peer (P2P) lending is a fast-growing financial technology (Fintech) trend, attracting many investors. Studies on P2P-lending have focused on limiting asymmetric information or determinants of default. However, limited research has focused on the future of P2P-lending as a relevant asset class for investors and how macroeconomic conditions, regulation and future uncertainties in the market will affect the attractiveness of the asset class.

Using a sample of 615,573 loans from the U.S. P2P-lending platform LendingClub, this study employs a four-part methodology to analyze and compare the attractiveness of the P2P-lending market with traditional credit asset classes in terms of their risks and their returns. In particular, Part I and Part II apply logistic regression models to determine the characteristics of default. The subsequent parts (III and IV) calculate the expected return of LendingClub's investors and analyze the relationship between risks and returns with other credit assets. Specifically, we look at the expected return, probability of default, Loss Given Default and Sharpe ratio. Lastly, supplementing our empirical findings, we present the future uncertainty of regulation and changes in the competitive environment.

We find that grade A loans on LendingClub are equivalent to Junk bonds and conclude that P2P-lending is a relevant asset class for risk-seeking investors. In light of the rapid growth of P2P-lending, the results from our methodology suggest that irrationality, lack of financial expertise, as well as herding behavior, are characteristics explaining P2P-lending investors. Additionally, accounting for the macroeconomic factors, this study shows that the default rate of loans has a significant negative relation to economic downturns. Considering the future risks and uncertainties in regards to macroeconomic conditions, new regulations and changes in the market, this study shows that the risks associated with P2P-lending are far greater than its returns and that a rational investor should in theory not be choosing P2P-loans over government and investment grade corporate bonds.

Abbreviations

AUC	-	Area Under The ROC Curve
CAGR	-	Compound Annual Growth Rate
CD	-	Certificate of Deposit
CDS	-	Credit Default Swaps
CPI	-	Consumer Price Index
DTI	-	Debt to Income
FN	-	False Negatives
FP	-	False Positives
GDP	-	Gross Domestic Product
LGD	-	Loss Given Default
LMP	-	Linear Probability Model
ML	-	Maximum Likelihood
OLS	-	Ordinary Least Squared
P2P	-	Peer-to-Peer
ROC	-	Receiver Operating Curve
ROSE	-	Randomly Over Sampling Examples
SEC	-	Security Exchange Commission
TN	-	True Negatives
TP	-	True Positives

Contents

1 Introduction

In the last decade, we have seen a rapid growth in technology and digitization. These new information technologies are a disruptive force on existing industries and their standards (Maynard, 2015). Financial technology (Fintech) is recognized as one of the most important innovations in the financial industry and is quickly evolving (I. Lee & Shin, 2018).

Among the first to feel the substantial threats of the growing Fintech industry was the banking sector. The 2008-2009 financial crisis had a strong impact on banking institutions around the world (Haas & Horen, 2012) and following the crisis, weak balance sheets and new regulations gave banks limited lending opportunities (Turner, 2018). Further, banks were forced to drop their interest rates to a historic low, leaving investors looking for new investment opportunities. The low return on bank investments as well as the difficulties borrowers faced obtaining loans from banks served as the base for the growth of the alternative Peer-to-Peer (P2P) lending. P2P-lending start-ups utilized this opportunity and created business models which avoided the regulations and requirements that banks were being held to (Desai, 2015).

Since the launch of the first P2P-lending platform Zopa in 2005, platforms have emerged around the world (H. Liu, Qiao, Wang, & Li, 2018). A report from 2015 showed that savings and investment technologies such as P2P-lending represented 16.7% of Fintech products, making it the second most popular product group after money transfers (Hatch, Nikhil, & Gulamhuseinwala, 2015). Going forward the industry expects a compound annual growth rate of 48.2% between 2016-2024 (Bajpai, 2016). The American platform LendingClub itself, has issued loans for a total value of $41.6 billion by February 2019 facing a 82.9% growth rate since 2012 (*Lending Club Statistics*, 2019). The industry's quick growth shows that P2P-lending is a service with a growing demand.

P2P-lending, also known as person-to-person lending, is an emerging asset class for investors. Through online platforms P2P-lending allows individuals to directly lend and borrow from each other without a traditional financial intermediary (Guo, Zhou, Luo, Liu, & Xiong, 2016). These online operations provide cheaper and faster lending services than traditional financial institutions. This competitive advantage benefits both borrowers and lenders. The borrowers are able to get uncollateralized loans and pay a lower rate on P2P-lending platforms (Emekter, Tu, Jirasakuldech, & Lu, 2015). These loans are often used to finance smaller financial expenses such as existing credit card debts, education, and weddings (*Lending Club Statistics*, 2019). At the same time, the platforms provide lenders with the opportunity to earn higher rates of return compared to other credit assets such as corporate bonds, government bonds or certificate of deposits (CDs) (Emekter et al., 2015). Since the lender invests money in loans to borrowers, we will use lenders and investors interchangeable when referring to the P2P-lending market.

As a relatively new asset class with an impressive growth rate over the years, there are reasons to raise questions about its future. Will investors and borrowers continue to be drawn to P2P-lending? Are there more risks related to investing in P2P-lending than investors are aware of? The literature around P2P-lending has developed throughout the years, and many of these questions are raised. However, researches stress the need for further knowledge in several areas, including investor preferences, new regulations and the spillover effects of a recovering financial system (Moenninghoff & Wieandt, 2013; Wei & Lin, 2017).

The impressive growth of the P2P-lending market shows that investors view the market as an appealing asset class. The P2P-lending market is known to provide investors with high fixed returns. Despite thorough research, few seem to have analyzed whether these high interest rates justify the investors appeal for P2P-lending. According to the financial theorist William Sharpe, investors should evaluate their investment alternatives by their risk-adjusted return (Sharpe, 1966). Further theories express that high risk investments must compensate investors with higher returns (Arrow, 1971). The young age of P2P-lending and the gap in the literature around its performance, leave plenty of room to analyze the characteristic of its risk-return relationship. Particularly, whether investors are rationally investing in P2P-lending because of the high interest rate or if the underlying risks are driving the high interest rates. Therefore, in order to analyze the future appeal of the asset class it necessary to have a clear understanding of the risks of P2P-lending and the characteristics of its investors.

An important thing to notice when evaluating the future P2P-lending markets and its investment opportunities, is that most P2P-lending platforms have not been stress tested through the economic cycle (Tikam, 2019). By investing in P2P-loans investors choose the interest rate on their investment and contingent on no defaults, enjoy a fixed return. If however, P2P-lending proves to be vulnerable during downtime, the landscape could change drastically. During a recession, economies face higher unemployment and the income level typically falls (Jenkins, Brandolini, Micklewright, & Nolan, 2012). As a result, individuals have less liquidity and have greater difficulty meeting their debt obligations. Hence, future macroeconomic conditions may affect the default rate among borrowers and thus reduce the investor's profitability.

Following the discussion on P2P-lending's risk and returns, a subsequent thought is how P2P-lending compares to investments in other asset classes. The rapid growth suggests that P2P-lending is an equivalent or better investment than other traditional asset classes. Thus, in order to make inference about P2P-lending's future relevance, and applicability as an investment alternative, one must compare the risks and returns of P2P-lending to other asset classes.

The rapidly changing global economy is another reason to further research P2P-lending. Traditional financial institutions are stabilizing, and interest rates are rising again, leading to more appealing bank returns. Since investors bear the entire credit risk in P2P-lending, investors are likely to go back to more tried and tested situations with banks (Guillot, 2016). Furthermore, this movement is anticipated because of the risk-averse nature of most investors (Ackert & Deaves, 2010). Moreover, there is uncertainty regarding the position banks will take in the future. They may either try to compete with P2P-lending and their technology or enter partnerships with them.

A popular claim in the Western world is that regulations allowed the P2P-lending business model and concept to take place (Adriana & Dhewantoa, 2018). Not only because of the restricting regulation on traditional institutions but also by the limited regulatory framework on P2P-lending. As the market continues to grow in size so do the accompanying risks (Verstein, 2011). In order to compensate for this increase in risk, the market is in need of new regulations. The regulators will have the responsibility to stabilize the market order and maintain the investor's interest (Adriana & Dhewantoa, 2018). However, these potential regulations will likely try to mitigate risks and can, therefore, have drastic effects on the P2P-lending market. Recently China introduced tighter regulations on their local P2P-lending market. Following these new regulations, the total number of P2P-lending operators in China dropped by more than 50% after a wave of defaults (A. Liu, 2019). The event in China shows that introducing new regulations can make the asset class less appealing.

The issues addressed so far represent the many uncertainties associated with P2P-lending. Intensive research on the P2P-lending market reveals a clear gap in the existing empirical studies, as few have concentrated on the future of P2P-lending from the perspective of an investor. Further, we emphasize that in order to understand the full picture of what drives the expected returns of the market, it is fundamental to analyze the underlying risks of P2P-lending. This analysis includes identifying the drivers of default with respect to the loan characteristics and the effect of the macroeconomic conditions. Thus, in this paper, we investigate how borrower characteristics, regulations, competition, and the economy's effect on the P2P-lending market can change an investors incentive to invest in this asset class.

1.1 Research Question

Based on the above background and motivation, this thesis aims to get insights into the future risks of the P2P-lending market. The ultimate goal is to assist investors in making wise decisions about their future investments. The research question will act as the core thought throughout this thesis, and guide the overall direction of our analysis. Through the following research question, we will analyze the P2P-lending market to see what factors determine the future attractiveness of P2P-lending in regards to both risk and returns.

"Is P2P-lending a relevant asset class for investors?"

1.2 Structure of the Paper

The rest of the paper is structured as follows. A literature review is provided in section 2. Next, a brief overview of the P2P-lending market and the platform LendingClub is found in section 3. Further, section 4 covers our data collection, description and pre-processing, as well as relevant conceptual definitions. Section 5 covers an exploratory data analysis to provide the readers insight to our dataset. Section 6 presents a theoretical framework to give a better understanding of the theories applied in our empirical study. An outline of our methodology is presented in Section 7. The methodology is divided into four parts. In Part I, we analyze the characteristics that determine loan default on LendingClub's platform. Further in Part II, we test whether the macroeconomic condition, has any predictive power in explaining loan defaults. Part III, calculates the expected return of LendingClub's loans. Lastly, in Part IV we analyze the relationship between LendingClub's grades and credit ratings from other asset classes. Following our methodology, we share our findings and empirical analysis in section 8. Next, section 9 presents a detailed outline of the future uncertainties of P2P-lending. Section 10 presents a formal discussion of the future of P2P-lending as a relevant asset class for investors. Lastly, section 11 includes the final conclusion on our work and areas for further research.

1.3 Delimitation

This thesis will focus on the largest P2P-lending platform, LendingClub. They have a database with the borrower and loan characteristics for all loans issued between 2007 and 2019, which is our primary source of data. LendingClub offers their borrowers loans with 36 or 60-months maturities. Because there is a larger number of observations available for loans with 36-months maturity so to avoid sample bias we delimit our analysis to these loans. Further, LendingClub issues loans to both consumers and small businesses. For our study, we focus exclusively on consumer loans. To avoid inconsistencies and sample bias, we limit our analysis to include individual loans, as LendingClub has not issued a significant enough amount of joint loans to conduct any inference.

To ensure that we are consistent in our analysis, we continue to focus on the American investor when evaluating alternative asset classes. For cohesion, we focus on investment assets in the credit market, specifically government bonds, corporate bonds and certificate of deposits (CDs). The 3-Year Treasury bond is used to represent the government bond class. An index representing each grade serves as our corporate bonds. We also consider investing in traditional banking institutions as an asset alternative. For simplicity, we look at the rate on CDs.

2 Literature Review

Our literature review begins by providing an overview of the existing research on P2P-lending. Besides presenting a summary of these findings, we present relevant literature on traditional asset classes. Including literature on other credit assets allows the reader to understand where the existing literature of P2P-lending fits into the greater context of financial theories and literature.

2.1 Literature on the Peer-to-Peer Lending Market

2.1.1 The Emergence of Online P2P-Lending

The early research on P2P-lending focused on investigating the economic incentives and conditions that allowed peer group lending to emerge as a concept. Peer group lending first emerged in the local communities of underdeveloped countries. The idea of peer group lending in local communities attracted the first research in this area and later expanded to the rest of the world. Conlin (1999) developed a model to explain the existence of peer group micro-lending programs in the U.S. and Canada. His findings showed that the goal in Canada and the U.S. was to increase entrepreneurship and self-employment. Through these programs, entrepreneurs who were considered too risky by the bank were able to receive funding. Furthermore, Humle (2006) studied how P2P-lending reemerged in the UK by looking at the P2P-lending company, Zopa. They find that P2P-lending is in the process of creating new ways of using and interacting with financial services. Moreover, they suggest that the emergence of P2P-lending is a direct response to social trends and the demand for new forms of relationships in the financial sector.

2.1.2 Asymmetric Information

Much like in the markets for other asset classes, there has been a significant amount of research on the presence of asymmetric information in the P2P-lending market. Research from traditional markets shows that in the presence of asymmetric information, investors cannot always distinguish between high-risk investments and low-risk investments (Jaffee & Russell, 1976). E. Lee and Lee (2012) claim that the problem of asymmetric information between the lender and the borrower is more severe in P2P-lending markets than in traditional markets. Klafft (2008) supports this claim by suggesting that since individual lenders in P2P-lending markets lack financial expertise and since the lending experience takes place in a pseudonymous online environment, lenders face a larger information disadvantage than in traditional lending markets. The consequences of asymmetric information between borrowers and lenders create market inefficiencies (Jaffee & Russell, 1976). Reducing information asymmetries would lead to an easing of lending standards and an increase in the volume of loans (Dell'Ariccia & Marquez, 2006; Kaminsky & Reinhart, 1999). Further, the presence of asymmetric information can lead to enhanced costs and deficient loan contracts (Bianco, Jappelli, & Pagano, 2005; Christie, 2013).

In addition to the literature on the presence of the asymmetric information, a fair amount of work tries to explain how information asymmetries can be mitigated (Chen & Han, 2012; Iyer, Khwaja, Luttmer, & Shue, 2009; Serrano-Cinca, Gutiérrez-Nieto, & López-Palacios, 2015; Yan, Yu, & Zhao, 2015). As a new asset class, Freedman and Jin (2008) explained how the first P2P-lenders lacked experience in evaluating the market's risks and drastically underestimated the borrower's risk. By examining ex-post performance data from Prosper, they found that lenders learn to shy away from risk over time. They emphasized that learning by doing plays an important role in addressing the asymmetric information problem. Chen and Han (2012) and Serrano-Cinca et al. (2015) both focus on how platforms provide lenders with information about borrowers and their loan purposes in order to mitigate these problems. Both articles explain how this information can either come from the risk grades given by the platform, or through credit scores provided by external third parties. Adams, Einav, and Levin (2009) and Weiss, Pelger, and Horsch (2010) examine how information asymmetries can be mitigated through screening. They found that within Prosper's platform, screening potential borrowers can mitigate adverse selection. Further, they found that key financial characteristics ("hard data") is a particularly significant instrument in mitigating adverse selection. Iyer et al. (2009) examine the screening ability of lenders in P2P-lending markets in contrasts to the process of traditional lending markets. The authors find that in addition to using standard financial information, P2P-lending companies use non-standard "soft" information in their screening process. This soft information is especially beneficial for low credit borrowers as it mitigates asymmetric information and increases their chances of receiving a loan. This soft data can be pictures, text descriptions and other information the borrowers voluntarily provide. Building further on this, Yan et al. (2015) investigates how signaling and search cost are reduced by using big data analytics for credit risk management. They find that big data analytics enables P2P-lending platforms to analyze more dynamic data points when evaluating credit risk. This data utilization improves the quality of the data and as a result, reduces information asymmetries through a more precise analysis.

2.1.3 P2P-Lending Benefits

Several studies have analyzed the hypothesis that P2P-lending benefits both the lender and the borrower (Klafft, 2008; E. Lee & Lee, 2012; Slavin, 2007). One benefit of the P2P-lending markets is the elimination of expensive third-party intermediaries. This elimination allows P2P-lending markets to have lower transaction costs compared to traditional lending markets (E. Lee & Lee, 2012). Slavin (2007)'s work provided an early insight into the benefits of using Prosper as a platform for lending and borrowing. He concluded that a major benefit is that P2P-loans generate higher returns for investors and are cheaper for the borrower. He also found that both parties favored the loan application, claiming the process to be fair as it is visible for all parties.

Luo, Xiong, Zhou, Guo, and Deng (2011)'s work shows that eliminating the financial institution benefits the investor. Research of traditional financial markets highlights capital structure as an indicator of a institutions financial position (Frank & Goyal, 2007). Thus, by eliminating the firm, the value of an investment will not be influenced by changes in the capital structure. Further, in traditional financial institutions, the determinants of lending may be affected by their managers own incentives. Since loans with higher risks give higher rates of returns and managers are often evaluated based on the institution's performance, the manager may have an incentive to take on more risk than optimal (Jensen & Meckling, 2012). An institution's risk-management standards may, therefore, be affected by the management's decision to take riskier loan positions in order to maximize the firm's value and their own compensation (K. J. Murphy, 2013).

2.1.4 Determinants of Lending

As a new asset class, it is necessary to understand what determines the lending decisions of P2P-lending investors. Once we have understood these determinants, we can proceed to evaluate the future of this alternative asset class. Traditional studies show that risk and return are two critical factors influencing investment decisions (Fama & Macbeth, 1973). Klafft (2008) found that in order to remain operating, P2P-lending platforms depend on rational, risk-neutral and profit-oriented investors.

When a market is not efficient, such as a P2P-lending market suffering from problems like information asymmetry, trust is found to an important determinant in loan funding (D. Liu, Lu, & Brass, 2015). Pavlou (2003) finds that trust enables lenders to overcome the uncertainties involved in loan transactions. Further, Chen, Lai, and Lin (2014) and Duarte, Siegel, and Young (2012) found trust between the borrowers and the investors to be a significant factor affecting the investors lending decisions. In particular, research found that characteristics such as the credit score of borrowers, default rates, and interest rates increase the trustworthiness of the borrower and thus, increase the number of loans funded (Bachmann et al., 2011; Chen & Han, 2012). Meng (2016) examined the determinants of lending decisions for Chinese P2P-lenders. Besides the factors found in previous studies, he found three additional factors to have a strong impact on a lenders decision. First, safety protection and service quality provided by the platform revealed positive impacts on the lender's willingness to fund loans. Moreover, Meng (2016) also finds that low transaction fees influence the lender's decision making.

When deciding whether or not to grant a borrower with a loan, a financial institution will evaluate the applicant's financial strength in regards to their existing portfolio. Wilson (1998) provides empirical evidence on how banks diversify their loans to reduce risk. The same result has been found for individual investors (Guo et al., 2016). Möllenkamp (2017) finds that alike traditional markets, P2P-lenders are risk averse and will try to minimize their investment risk by decreasing the overall default risk and only invest in the most attractive loans. Luo et al. (2011) looks at the loans as the investees (i.e., stocks, bonds, etc.) in the P2P-lending market and tries to enhance their investment decisions by looking into the characteristics of the investee which can be quantified by statistics.

They created an investment decision model that identifies the best loans and match it with the investor's risk profile to improve their investment decisions.

2.1.5 Herding Behavior

Authors in the field of behavioral economics have studied the presence of herding behavior in P2P-lending markets (Herzenstein, Dholakia, & Andrews, 2010; Krumme & Herrero, 2009; E. Lee & Lee, 2012). Banerjee (1992) first connected the psychological theory of herding behavior to financial markets by modeling an individual's investment decision with the actions of previous investors. Later work has empirically tested his theory and detected herding behavior in financial market investors (Graham, 1999). Bikhchandani and Sharma (2000) found that in financial markets with imperfect information the information disadvantaged investors tend to herd.

In the framework of P2P-lending, herding behavior bias is defined as the tendency to invest in partially funded loans while ignoring more attractive unfunded alternatives (Dholakia & Soltysinski, 2001). Herzenstein et al. (2010) conducted an empirical study on P2P-lending and demonstrated that strategic herding behaviors exist. The authors argue that using strategic herding behavior is advantageous for lenders but only until full funding is reached. Lux (1995) formulates how herding behavior leads to equilibrium prices above their intrinsic value. His paper concludes that once returns stagnate, investors leave the market, causing the price bubble to burst and the market to crash. Further, Ngene, Sohn, and Hassan (2017) found that herding behaviors lead to structural breaks in financial markets. Others have empirically studied the role of herding behavior in financial crises and found herding to be a significant factor in predicting market crashes (Kim & Nofsinger, 2007; Singh, 2013).

2.1.6 Credit Ratings and Credit Scores

Credit scores are a widely used information source that investors examine before deciding on their investments. The qualities of traditional asset classes are assessed and scored to express their riskiness. Mester (1997) found that credit-scoring system allows the banks to categorize their loan applications in a greater range of creditworthiness and more efficiently than human judgment can. Research on both the traditional asset markets and the P2P-lending market find that those with better credit scores receive lower interest rates than those with worse credit scores (Freedman & Jin, 2008; Schwendiman & Pinches, 1975). Empirical evidence also shows that it is easier for institutions, individuals, and firms to receive funding when they have better credit scores. This is found in traditional markets (Jaffee & Russell, 1976), as well as in P2P-lending markets (Freedman & Jin, 2008; Y. Zhang, Li, Hai, Li, & Li, 2017).

2.1.7 Investment Risk

Investment risk is extensively covered within psychological, economic and financial literature. One class of literature focuses on risk strategies and how to minimize risk exposure. Olsen (1997)'s study shows that investment risk appears to be comprised into four; the potential for a large loss, the potential for below-target return, the feeling of control, and the perceived level of knowledge. In the context of lending, the potential for a large loss is the most prominent risk for an investor. Early methods measured an individual investors risk by variance, skewness and other return distributions (Alderfer & Bierman, 1970; Cooley, 1977). Later, methods use the concept of utility and motivate that a rational investor maximizes their expected utility when making an investment decision (Pennacchi, 2007). An investor's expected utility is calculated by evaluating their expected return accounting for the probability of a loss (Ackert & Deaves, 2010). Sharpe (1966) introduced the concept of risk-adjusted return to evaluate the performance of an investment.

P2P-lending involves almost all major risk types such as credit risk, liquidity risk and market risk (Moenninghoff & Wieandt, 2013). Although P2P-lending platforms offer tools such as credit grades and borrower characteristics to help mitigate risk, the investors are solely exposed to the default risk of their investments (Moenninghoff & Wieandt, 2013). Several papers have calculated the determinants of default within P2P-lending platforms (Emekter et al., 2015; Serrano-Cinca et al., 2015; Tao, Dong, & Lin, 2017). In their work, Serrano-Cinca et al. (2015) examine the relationship between the grade, the interest rate, and the default rate. The authors found that loan purpose, annual income, current housing situation, credit history, and indebtedness all influence the default rate. Equivalently, Emekter et al. (2015) found that credit grade, debt-to-income ratio, FICO score, and revolving line utilization play an important role in loan default. In the Chinese market, Tao et al. (2017) found that owning a car and income are highly significant variables in predicting the likelihood of default. In addition, unlike other findings, they found that the credit grade assigned to an individual is not a good representation of the borrowers' creditworthiness.

Emekter et al. (2015) examine the return efficiency of LendingClub. Using default rates, they calculated the theoretical return a lender should receive for the risk they hold. Further, they compared these theoretical returns with the actual interest rate charged by LendingClub. They find that the likelihood of loan default increases with the credit risk of the borrowers. Moreover, they find the interest rates charged on high-risk borrowers are not enough to compensate for the higher probability of the loan defaulting. Golubnicijs (2012) performs an empirical risk analysis of the P2P-lending platform, Prosper. He finds P2P-lending to be an attractive investment alternative.

2.2 Literature From Other Asset Classes

After reading the literature available on P2P-lending, we found that there are several areas of research available in the context of other asset classes that are not yet covered within P2P-lending markets. We also reflect that findings from traditional markets have been consistent with those from the P2P-lending market. This section of our literature review will, therefore, cover financial literature that is not directly related to P2P-lending but can generally be applied to credit assets.

2.2.1 Impacts of Macroeconomic Factors

Investment decisions are affected by both the current and the future macroeconomic environment. Earlier research by B. S. Bernanke and Blinder (1992) analyzed a bank's lending activity during monetary policy shocks and found a negative relationship between a bank's lending activity and monetary contractions. Using these results as a basis for further research, later literature showed that banks carrying poor loan qualities are more sensitive to monetary shocks than better capitalized competitors (Peek & Rosengren, 1995). Rigobon and Sack (2004) explored the relationship between monetary policy and asset price volatility. They found a negative relationship between short term interest rates and asset prices.

Another well-studied macroeconomic variable is the business cycle. Bikker and Haixia (2002) shows how an economy in the downward slope of the business cycle is plagued by higher risks associated with their loans, higher capital requirements and overall a smaller supply of credit. Additionally, their paper studied investor returns and macroeconomic shocks by empirically testing stock market volatilities with differences in macroeconomic conditions, using GDP growth as a proxy variable. Others have studied bond returns during the different stages of the business cycle (Cochrane & Piazzesi, 2005; Ielpo, 2012). Reinhart and Rogoff (2009) studied the aftermath of financial crisis and found asset prices as well as economic indicators to be suppressed in the succeeding years following the crisis.

The causes of financial collapses and recessions is another frequently researched area. Lettau and Ludvigson (2014) found empirical evidence that macroeconomic shocks characterized both the 2000-2002 asset market crash and the 2007-2009 crash. During credit market booms lending to the private sector increases rapidly. Gourinchas, Valdes, and Landerretche (2001) empirically analyzed the relationship between lending booms and financial crisis. They found that a lending boom does not significantly worsen the financial situation of an economy. However, when comparing their results across the world, they found that a financial crisis follows lending booms in Latin America. In short, there is evidence in the literature that geographic location is significant variable in determining the success of lending.

The literature on economic fluctuation from before the 2008 market crash gives little weight to financial markets in determining fluctuations in the business cycle (Ibrahim & Shah, 2012). In light of recent financial events, academic research has moved to recognize the significant relationship between financial markets and financial crises. Cargill (2000) studied the Japanese banking crisis of the early 1990s. His work shows how price bubbles, bad loans, and bank policies led Japan into a bank crisis and later a full financial crisis. Other works on different markets and asset classes find similar results, concluding that macroeconomic variables are significant in determining the outcome of lending (Athanassakos & Carayannopoulos, 2001).

Another wave of literature focuses on how the macroeconomic environment can lead to contagion risk. Connolly and Wang (2000) show how the likelihood of a shock and the potential impact of that shock, lead to the risk of contagion within a system. Allen and Gale (2000)'s paper proposed market structure as a determinant for contagion within the financial systems. Others have looked at contagion between bank lenders as a result of being hit by the same shocks from the economy (Ladley, 2013; Miller & Stiglitz, 1999). Further, Cornell and Green (1991) studied the risk exposure on different bond classes and found low-quality corporate bonds to have higher exposures to systemic risk than other bond classes.

2.2.2 Impacts of Regulation

Research shows that the Fintech industry in western countries has been motivated primarily due to trust issues in traditional financial institutions and because regulations have created an unserved market (Adriana & Dhewantoa, 2018). Wang and Hua (2014), explain that due to new risk exposures the entire P2P-lending market needs a reshuffling.

Sundararajan (2014) explains how P2P-business markets, in general, create new roles in the financial market and are misaligned with existing guidelines. In their research, Moenninghoff and Wieandt (2013) conclude that impending regulations will decide the future of P2P-lending. J. Murphy and Davis (2016) express that in regards to traditional investment alternatives, P2P-lending markets do not have a fundamental distinction between a market operator and a financial service provider. He claims that capital markets must go through a complete restructuring to allow for separate regulations. In 2010, the U.S. requested a study to evaluate the regulatory options for P2P-lending (Chaffee & Rapp, 2012). The attempt was to increase consumer protection and corporate responsibility.

Since 2015, the Chinese government has intensified its regulations on debt and financial risk. Nemoto, Huang, and Storey (2019) found that the increased regulation caused a wave of defaults in Chinese P2P-lending and a huge investor flight. Further, Adriana and Dhewantoa (2018) determined that the investors' inability to comply with the new regulations caused lending to drop. Tao et al. (2017), on the other hand, found that more regulations will cause the lending market to have less fraudulent behavior and bad debtors.

2.3 Our Contribution to Existing Papers

Concluding this section, the amount of literature on the phenomenon of P2P-lending and its particular characteristics has developed throughout the years. However, research in this field is still the an early stage characterized by a dominant presence of studies stemming from a psychological-behavioral background rather than from a financial one. In particular, most of the empirical studies have focused on determining the characteristics of default (Serrano-Cinca et al., 2015) or determining the characteristics of successfully receiving a loan (Bachmann et al., 2011; Meng, 2016). We observe a gap in the literature when it comes to analyzing the future of P2P-lending from the perspective of an investor. In relation to the presented literature Moenninghoff and Wieandt (2013) and Golubnicijs (2012) papers are closest connected to ours.

Moenninghoff and Wieandt (2013) conducted a study on the future of P2P-finance and emphasized the role of risk in the market. Their work focused on P2P-financing as a broad concept and did not limit their studies to an investors perspective or P2P-lending in general. Their paper looked largely at the stability of P2P-businesses and the threat of regulation. In contrast, they did not empirically compare their findings to other asset classes or their future risks and returns.

Golubnicijs (2012) compares investing in the P2P-lending market to investing in the stock market. He specifies a model for predicting default rate and finds an investor's expected return for both asset classes. Building on the same basis as his paper, our work differences from his in several ways. First, we will use logistic regression to determine default on the P2P-lending platform. Second, we will introduce macroeconomic factors to explore whether existing models are biased due to omitted variables. From what our research shows, we are the first to empirically study and analyze the macroeconomy's effect on the attractiveness of P2P-lending. Our presentation of the literature shows that these effects have previously been studied on other asset classes and found to be significant. Third, we consider other factors such as regulation, in our evaluation of P2P-lending as an asset class. Again, past literature has inspired this inclusion. Past events around the world have shown how introducing regulation can alter an asset market's characteristics. We have presented literature with these findings both within the P2P-lending market and in other markets (Chaffee & Rapp, 2012). Also, we found that early literature on the P2P-lending expresses concern for future regulations (Moenninghoff & Wieandt, 2013; Verstein, 2011). Since these were published, regulations have emerged around the world. Reflecting on these new regulations, we found there is a gap in the literature, as no one has gone back to reevaluate the effects of regulation. Our paper will attempt to fill these gaps. Fourth, we do not compare P2P-lending to the equity market but rather to other credit markets.

3 LendingClub and the P2P-Lending Market

LendingClub was founded in San Francisco, California in 2006, a few years after the first online P2P-lending platform, Zopa emerged. In 2015, LendingClub became the worlds largest P2P-lending platform and has remained the largest since (Nowak, Ross, & Yencha, 2018). Their loan amounts range from $1,000 to $40,000 and as of February 2019, they have funded $41.6 billion in total loans [1]. Figure 1 shows the amount of total issued loans by LendingClub and illustrates the massive growth the platform has had since its establishment.

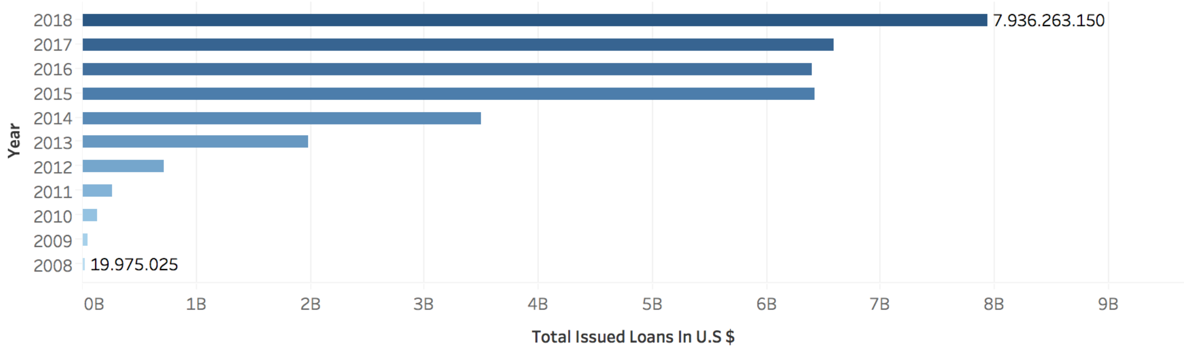

Figure 1: Total Loans Issued On LendingClub

Originally LendingClub only issued 36-months loans, but in 2010 they expanded and issued 60-month loans as well. LendingClub allows borrowers to repay their loans early without additional costs. In December 2014, LendingClub was the first P2P-lending platform to go public. Their Initial Price Offering (IPO) was priced at $15 per share, giving the company a total value of $5.4 billion (Reuters, 2014). Unlike other platforms, such as Prosper, LendingClub offers joint-loans were borrowers can apply for loans together.

When setting interest rates on loans LendingClub operate with a base rate of 5.05%. To find the interest rates offered to individual borrowers, risk adjusted rates are added to the base rate. These adjustment rates are based on the borrower's credit grade and are created to cover expected losses. LendingClub rank their loan applications on a grading system that ranges from A to G, where A represents the highest quality borrowers. Each

[1] All information in this section is taken from LendingClub's website (LendingClub, 2019), unless otherwise stated

of these lettered loan grades are divided into five sub-grades. Thus, in total there are 35 sub-grades to express the credit risk of a borrower.

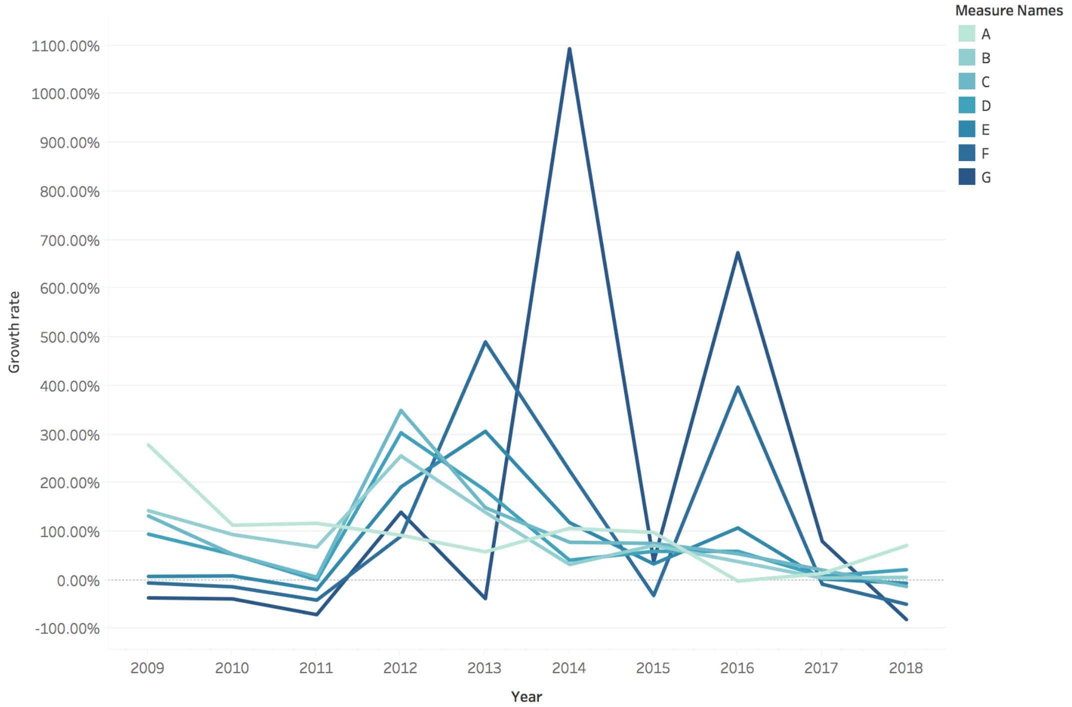

Figure 2: Growth Rate of Issued Loans by Grade

Figure 2 shows the growth rate of the total loans issued in each grade by LendingClub since their establishment. From this figure, it is clear that the issuance of grade A loans has been relatively steady. The less creditworthy grades, on the other, hand have fluctuated considerably.

3.1 The Rise of P2P-Lending in The U.S.

Young innovative firms like LendingClub play a key role in modern knowledge-based economies because of their radical innovations (Block, Colombo, Cumming, & Vismara, 2018). The landscape of entrepreneurial finance has changed over the last decade especially in the aftermath of the financial crises. The following section will describe the underlying factors explaining the emergence of P2P-lending in the U.S. Specifically, we will distinguish between economy-related factors, regulatory factors, technology factors, and disintermediation.

Before the financial crises, the banks were close to a monopolist in lending to businesses and individuals. As outlined in the literature, after the financial crises the regulation of financial institutions intensified with a strong focus on the banks (Freedman & Jin, 2008). During the crisis, The Basel Committee strengthened the Basel II capital framework, and in 2010 they issued the Basel III framework. These enhancements were a part of the effort to strengthen the regulation and supervision of internationally active banks and included stricter requirements for the minimum capital that a bank has to hold (BIS, 2018). Thus, to comply with these new regulations, the banks were required to tighten their lending activities. These regulations created the funding gap P2P-lending companies like LendingClub took advantage of.

In addition, the financial and subsequent economic crises drove the central bank's interest rate to a historic low. The low interest rates made investments in government and corporate bond less attractive and led investors to seek other investment opportunities (Block et al., 2018). With the stock market being in a downturn, investors started to shy away from the volatile stock market and saw P2P-lending platform as a better investment opportunity (Barry, 2018). This increased the chances for innovative, high-risk ventures to receive capital.

Regulation is also seen as a reason for the emergence of the P2P-lending market. P2P-lending became attractive because they operate outside the scope of strict financial regulation arising after the financial crisis (Cumming & Schwienbacher, 2018). Thus P2P-lending platforms could legally serve the market that banks could not.

Moreover, new technologies have been central to the emergence of alternative financing firms, including P2P-lending. These market platforms would not be available without the new information and communication technologies such as the internet and the new ways of utilizing data. Big data and advanced analytic provided new ways to assess risk and treat financial information. Cloud infrastructure removes the need for hardware procurement, infrastructure engineers or data center, allowing companies to scale up and down without legacy costs. The vast amount of hard and soft data available makes it easier to verify the reputation and the trustworthiness of any individual reducing the verification cost (Goldfarb & Tucker, 2017). Technology also allows platforms to make faster financing decisions, engage more proactively with customers and run the operations at low cost-to-income ratios (Tikam, 2019).

The growth of the internet and financial innovation provided the ability to countervail the problems of traditional institutions. Financial intermediaries are meant to reduce information problems and help demand and supply for capital. However, their activities are costly creating sub-optimal solutions (Block et al., 2018). Innovations like P2P-lending platforms by-pass intermediaries so that investors and borrowers meet directly. Their online platform creates new opportunities for entrepreneurs and more risky consumers to raise capital and non-professional investors disintermediate their investment.

3.2 LendingClub

3.2.1 Business Model

LendingClub[1] operates as an unsecured loan issuance mechanism. They use technologies and algorithms to match lenders and borrowers. In their Form S-1 (Registration Statement) filing to the SEC, they outlined the key elements of their technologies. They ranged from highly automated processes, scalable infrastructures, proprietary fraud detection, data integrity and security, and application programming interface.

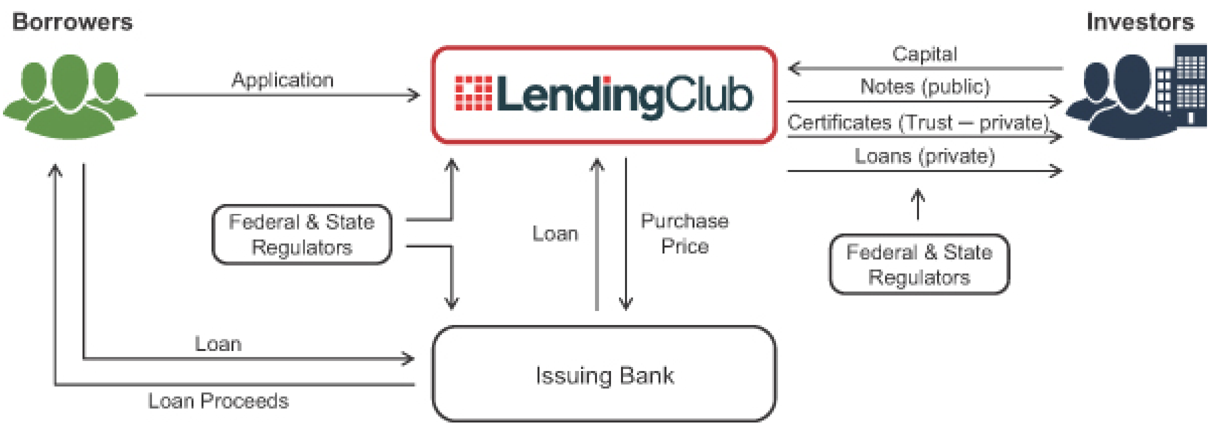

Figure 3: LendingClub's Business model

Figure 3 illustrates LendingClub's business model. Their loan issuance process can be summarized into six steps.

First, a borrower opens an account on LendingClub's platform. In this process, they are required to provide personal information and loan characteristics such as loan purpose, loan amount and annual income.

Second, LendingClub performs a background check, by verifying the information the loan applicant provides. Further, they perform a credit check to obtain information such as their FICO score from Fair Isaac Corporation. During this stage, the platform uses propriety risk algorithms that analyze the applicant's data. This data includes behavior data, transaction data, and employment information. Lenders may also be asked to provide additional documentation that helps identify them and their risks. Automated technologies will then perform a credit assessment on the applicant and determine the interest rate on their loans.

Third, if the applicant satisfies certain criteria, LendingClub will provide various loan offers. These loans will differ in loan terms, such as loan amount and interest rates. The borrower will then choose whether to accept one of the loans offered.

Fourth, LendingClub will add the accepted loan to a loan listing within their database. Investors can look through these listings and choose loans to invest in. These listings include the interest rate, loan term and borrower characteristics. Investors can invest in loans with minimum $25 dollar increments. If a loan receives full funding from investors, LendingClub's partner bank will issue the loan (Sethi, 2016).

Fifth, a few days later LendingClub will purchase the loan from the bank. Once they have purchased the loan, they hold the obligation of the loan contract.

In the **sixth** step, LendingClub distributes notes to each investor. These notes are unsecured notes and reflect the share of the loan that the investor funded (Nowak et al., 2018). After the final step of LendingClub's business model, the investors become the creditors, and hold all the credit risk. The borrowers make payments on their loans which are then transferred from LendingClub to note holders (Sethi, 2016).

The above business model illustrates how LendingClub's operations allow them to remain as a facilitator of loans without holding the credit risks that traditional institutions hold. P2P-lending companies have lower transaction costs than conventional financial institutions since they have a simpler business model. In particular, they do not capture deposits, are not under strict banking regulations and do not maintain idle balances.

Their role is to connect borrowers with lenders (Serrano-Cinca et al., 2015). In addition, LendingClub benefits from lower capital requirements than traditional institutions because they are not exposed to credit risk (Nash & Beardsley, 2015).

LendingClub's net revenue was $500.8 million in 2016, $574.5 million in 2017 and $694.8 million in 2018, showing impressive growth rates in recent years[1]. The platform is able to make money by charging both the lender and the borrower a fee for facilitating realized transactions (Galloway, 2009). They also receive transaction fees from evaluating and accepting applications for their bank partner to enable loan originations. Other sources of income are gains on sales of loans, interest income earned and fair value gains invested in by LendingClub. However, the transaction fees charged to borrowers and investors are still their greatest source of income. For the 2018 fiscal year, these fees represented 75% of their net revenue. According to their financial statements, the amount they charge in transaction fees is calculated based on the terms and characteristics of the loan. The fees range from 0% to 6% of the face value of the loan. LendingClub's primary expenses are sales and marketing (33%), other general and administrative expenses (28%) and engineering and product development (19%).

Although LendingClub's business model allows them to remain free of credit risk, it does not mean that they are entirely free of risk. In order to remain profitable, they are dependant on investors and their liquidity. LendingClub operates with a secondary market called The Note Trading Platform. Even though the platform is designed to provide investors with the chance to liquidate themselves, there is no guarantee that the notes will sell. Moreover, these notes are viewed as highly risky since only limited information is available in the secondary market. Thus, LendingClub is greatly exposed to liquidity risk because investors can stop funding loans at any time.

3.2.2 Competitive Environment

LendingClub's competitive environment consists of other online lending platforms as well as traditional financial institutions. Since LendingClub only operates for American customers, their competitors are institutions providing loans to the American customer base. Their closest competitor is the P2P-lending platform, Prosper. Because their loan terms are so consistent with each other, the two platforms compete on a rate basis. Other P2P-lending platforms have also emerged in the U.S. over the years. Among these are SoFi and Upstart (White, 2017). SoFi offers lower interest rates and higher loan amounts than LendingClub. For these reasons, SoFi might appeal to higher quality borrowers. Upstart, on the other hand, has a higher minimum rate than LendingClub and a higher maximum rate (White, 2017). This might appeal to higher risk borrowers. LendingClub state that they aim to provide loans to the highest quality applicants (Nowak et al., 2018). Although they operate on completely different business models, banks and other lending institutions cannot be excluded from the list of competitors. LendingClub together with the other P2P-lending platforms have grown rapidly over the last years, but still, only account for 37% of unsecured personal loans in the American credit market (Levitt, 2018).

LeadingClub leads the online P2P-lending market and is currently able to provide a differentiated lending experience compared to traditional institutions. LendingClub can provide funding for a wider customer class and still entice investors. Their large size and early start created economies of scale in comparison to other P2P-lending platforms. Further, because P2P-lending platforms are not required to hold the same amount of capital as banks, they are less restrained in their ability to give out loans. They are also not restrained by any loan portfolio regulations to determine the extent to which they can issue loans of different characteristics. Since loan providers are competing in the interest rates they provide their customers, being able to keep their costs down is vital and will determine who will prosper in the coming years. Banks and other financial institutions also have in recent years, heavily invested in technologies allowing their services and products to align further with the rising P2P-lending platforms. Industry experts have claimed banks and P2P-lending platforms will not substitute each other but rather complement each other and establish business models that work together (Tang, 2018).

3.2.3 Market Participants

P2P-lending is a two-sided market where lenders and borrowers are the main target groups of all platform activity.

Borrowers

LendingClub[1] has two types of borrowers divided into personal loans and business loans. Business loans regard small businesses up to $300,000 in funding. This paper will focus on personal loans. LendingClub defines personal loans as money borrowed in a lump sum, at a fixed rated and repaid in installments over the life of the loan. LendingClub has set restrictions about what borrowers cannot use a personal loan for, including investments, gambling, or anything illegal.

Lenders

For lenders, P2P-lending platforms can be seen as an investment class, where the investment risk is coupled to the credit rating of the funded loans (Bachmann et al., 2011). LendingClub divides their investors into two different segments, individual investors and institutional. Each segment follows their different requirements. Individual investors must be U.S. residents above the age of 18, with a social security number and a valid identity card. Unfortunately, not all states allow investors to participate in P2P-lending. Therefore, in order to invest, the investor has to reside in a state which approves investing in LendingClub. When opening an account in LendingClub, there is a requested initial deposit of at least $1,000 as well as some additional financial requirements depending on the state. Since LendingClub operates with a series of unsecured notes, investors have the opportunity to diversify their portfolio and earn competitive returns on consumer credit. This type of diversification has previously only been available to banks and other large institutions.

4 Data

Our motivation and relation to existing literature have now been outlined. We have also provided a detailed overview of the P2P-lending market and in particular our company of choice LendingClub. We will now move into our analysis. For our empirical study, we have compiled a dataset of loan characteristics and macroeconomic variables. In addition, we have collected performance data from corporate bonds, government bonds, and CDs. This section presents our data collection, pre-processing and limitations.

4.1 Loan Data

4.1.1 Dataset Description and Collection

We collect our loan data from the P2P-lending platform LendingClub. In order to provide investors with a fully transparent view of LendingClub's loan portfolios and their performances, their data is publicly available for download on their webpage. LendingClub is the industries largest platform and also have the largest database. Our proprietary data was downloaded in February 2019. The raw dataset contained 2,260,681 loans from 2007 to 2019. Our loan data can be sub-categorized into loan characteristic and socio-economic data. The loan characteristic data provides information on variables such as loan amount, interest rates and total payment amount. The socio-economic data, on the other hand, provides information on the borrower's characteristics such as employment, zip code and housing.

4.1.2 Data Pre-Processing

To ensure consistency in our analysis, we discard the 60-months loans from our dataset. Keeping the 36-month loans over the 60-months loans allows us to maximize our observations, since 60-months loans were only first issued in 2010. Additionally, loans from 2007 are excluded because they contain different borrower information than in the subsequent years. Further, loans that have not yet reached maturity are irrelevant for our study and thus, are excluded. In other words, we omit all loans issued after February 2016 since they do not mature before February 2019. In a further analysis of the raw data, we found a large amount of the loans issued in February 2016 to still be current, due to late payments. For consistency we, therefore, omit all 2016 loans. Our final dataset contains the

36-month loans issued between 2008 and 2015. The total number of loan observation in our dataset is 615,826. A summary table of the numerical data is presented in Appendix (A1.1).

In order to perform our analysis, we prepare the data with a thorough data cleaning process. First, we check our dataset for missing variables. In particularly we find a significant amount of missing observations in the following variables; *months since last delinquency*, *revolving line utilization rate* and *title*. To deal with these blanks loan observations with incomplete information are removed from our dataset. Removing these missing variables ensures that the variance is not impaired and does not compromise our dataset since the total observations deleted is small in relation to the size of the dataset. The same argument leads us to keep the missing variables for *length of employment*, as the number of missing observations is much larger and deleting them would lead to a large loss of information. Instead, we use coarse classification to bin the observations into groups where we place all the "n/a's" in their own bin called "missing".

Next, we evaluate our variables in order to determine whether to include them in our analysis. The original dataset consisted of 151 variables. However, many of them are not relevant for our analysis such as *member id*, *trade accounts* and *number of trades*. Keeping the aim of this study in mind, variables containing information not known at the time of the investment are removed. Subsequently, we find *loan description* to be incomplete and to provide similar information as *purpose*, and thus, is eliminated. Moreover, we check the number of unique values for each variable to analyze their information power and uniqueness. Variables such as *zip code* and *address state* have too many unique observations to include as dummies and are therefore eliminated. The variable *policy code* is removed as it consisted of only one observation and therefore provides no informative power.

To get better use of the loan information provided by LendingClub we create a new variable, *length of credit history*. This variable is calculated by subtracting *earliest credit line* from *issue date*. The variable *home ownership* originally consists of the six factors; mortgage, rent, own, other, any and none. The three later are undefined by LendingClub and therefore hard to use in our analysis. Therefore, they are removed from our dataset.

4.2 Macroeconomic Data

4.2.1 Dataset Description and Collection

We have collect our macroeconomic data directly from the Organisation for Economic Co-operation and Development's (OECD) database (OECD, 2019). The OECD is a large international organization and seen as a reliable source of data. We chose a quarterly frequency in the same time period as our loan data, 2008-2015. These variables are then added to our existing dataset. We incorporated the macroeconomic data to our existing loan data by matching the issue date of loans to the corresponding quarterly macroeconomic variables. Since LendingClub only issued loans to residents of the U.S., we limited our macroeconomic variables to reflect the U.S. economy. The macroeconomic data consist of the unemployment rate, GDP growth and the Consumer Price Index (CPI).

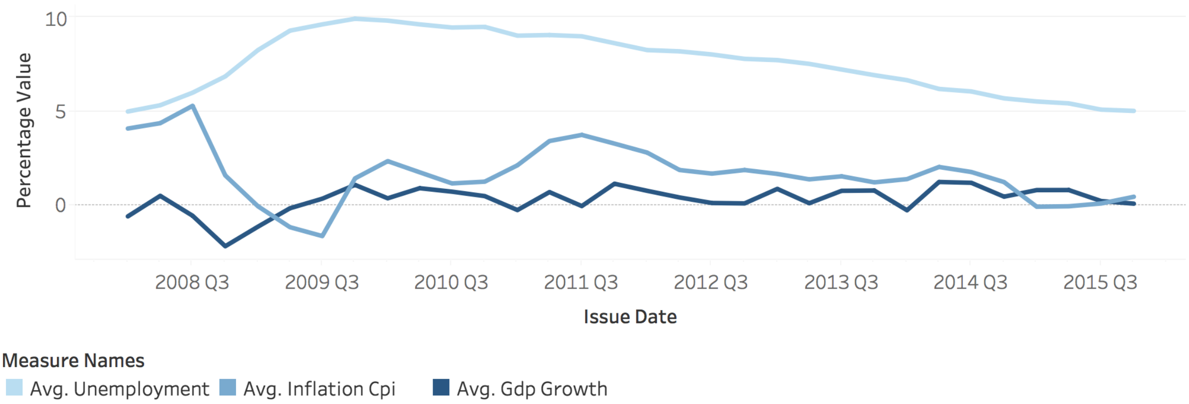

Figure 4: Evolution of the U.S. Economy

Figure 4 shows the development of the unemployment rate, the GDP growth and the CPI between 2008 and 2015. Out of the three variables, the unemployment rate has been the least volatile. The unemployment rate started at 5.0% in 2008 Q1 and increased to 9.93% by 2009 Q4. Unemployment remained high for a few quarters before reverting to a 5% level in the subsequent years. CPI, on the other hand, has been slightly more volatile. It started at near 5% in 2008 Q1 and peaked at 5.3% in 2008 Q3. During the financial crisis, the CPI quickly decreases to a low of -1.62% in 2009 Q3. Since 2010 and the recovery of the financial crisis, the quarterly CPI has fluctuated between 0% and 3.5%. Moreover, the GDP growth's range has also been more volatile than the unemployment rate. However, compared to CPI, the variance of GDP growth fluctuations is not as large. It went negative during the recession reaching its lowest point in 2008 Q4 at -2.16%. Subsequently, it peaked at 1.25% in 2014 Q1. The general trend since the financial crisis has been a GDP growth between 0% and 1%.

4.2.2 Choice of Market Indicators

CPI, GDP growth and unemployment rate are common indicators used to measure changes in the business cycle. As the creditworthiness of borrowers varies over the business cycle, there is a reason to believe these factors will affect lending rates (B. Bernanke & Gertler, 1995; Kiyotaki & Moore, 1997).

The CPI is used to represent the economy's inflation rate at the time of the loan issue. The inflation rate shows the rate at which the price for consumer goods and services rise. The inflation rate from OECD is measured as an annual growth rate and expressed as an index (OECD, 2019). Intuitively, when the price level in an economy increases, it means consumers spend more money on buying essential goods and services. Further, individuals might have less money to repay their debt (Sheheryar & Khan, 2015). Others have shown how increases in inflation cause a larger spread between the rich and the poor (Easterly & Fischer, 2006). The poor who tend to have lower credit scores will have higher probabilities of default. Monetary economics shows that there is a robust negative relationship between the inflation rate and the interest rate (Mishkin, 1992). Therefore, by testing for the significance and the effect of the CPI on Loan Status we aim to provide some intuition on the relationship between loan status and interest rate.

Economic theories highlight a significant relationship between the credit market and the level of unemployment in the economy (Kaminsky & Reinhart, 1999; Sinkey & Greenawalt, 1991). Gambera (2000) found that consumers are more likely to default on their loans when there is higher unemployment. For this reason, we download the quarterly unemployment rate for the U.S. for the years 2008-2015. Using the unemployment rate for our study allows us to determine whether these finding from traditional credit markets apply to P2P-lending. Furthermore, the labor market is highly relevant, given that we are analyzing uncollateralized consumer credit and loan payments depend on earned income (Dietrich & Wernli, 2017).

Lastly, we include GDP growth. GDP growth is a primary indicator of the performance and strength of the economy. A strong economy is associated with higher income and more consumption. Sheheryar and Khan (2015) found an inverse relationship between loan defaults in the banking sector and GDP growth. Further, they outline that higher GDP growth translates into higher incomes and strengthens the creditor's position to pay back loans. These findings suggest that a weaker economy leads to a higher rate of default.

4.3 Dependent Variable

Loan status is our binary dependent variable. The first part of our methodology is to determine which variables predict default. We use loan status as the indicator of whether the loan has defaulted or not. In the dataset *loan status* is composed of eight statuses: "Charged Off", "Fully Paid", "In Grace Period", "Late (31-120 days)", "Late (16-30 days)", "Does not meet the credit policy. Status: Fully Paid" and "Does not meet the credit policy. Status: Charged Off". LendingClub has provided investors with definitions and guidance to understand the status of their loans. A "Charged Off" loan, is a loan where the borrower has defaulted, and the loan will not be paid back in the full amount. A "Current Loan" is a loan that has not reached its maturity, is delayed or is currently being paid off. "In Grace Period", "Late (31-120 days)" and "Late (1-30 days)" are loans delayed on their installments. "In Grace Period" means borrowers are less than 15 days late on their payments, while the two other represent longer periods as indicated by the numbers in parenthesis. We remove all "Late", "In Grace Period" and "Current Loans", as we do not know the outcome of these loans, and whether or not they will be paid back. For our analysis, we use Default and Non-Default to represent loan outcomes. We categorize "Charged Off" and "Does not meet the credit policy. Status: Charged Off" as our defaulted loan observations. For our analysis, we treat these outcomes as dummy variables where defaulted loans are shown by binary outcome 1 and non-defaulted loans by 0. In our dataset, 13.9% of loans have defaulted, meaning 86.1% are successfully paid back. Figure 5 shows the percentage of defaulted and non-defaulted loans within each grade.

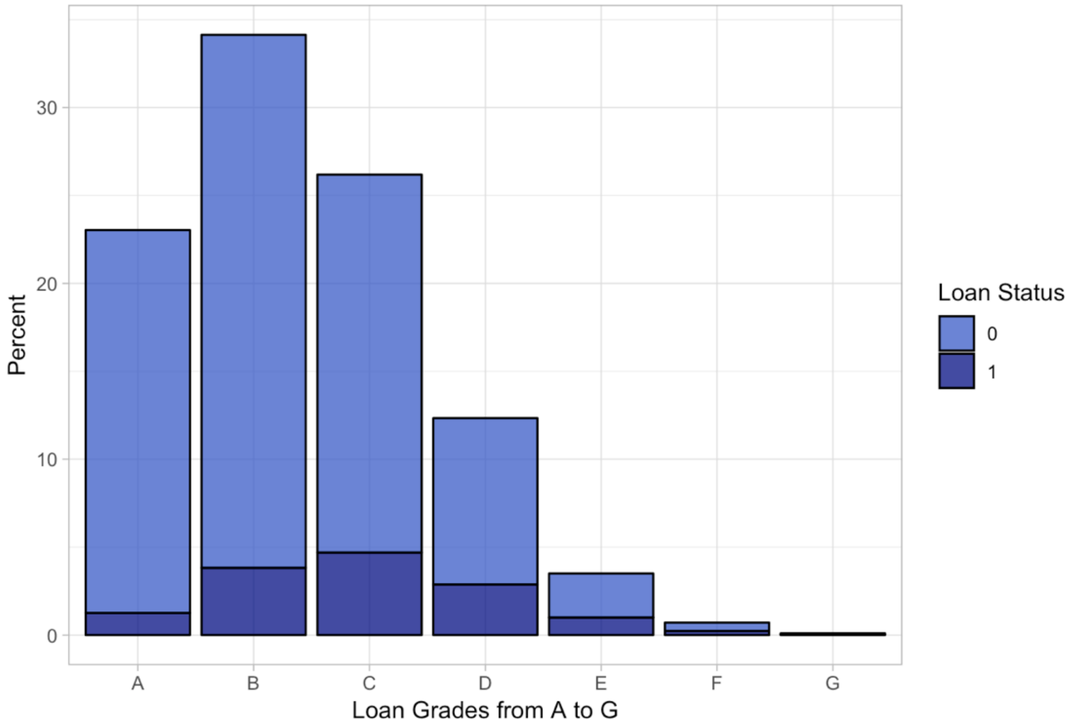

Figure 5: Distribution of Loans by Grading Scores and Loan Status

4.4 Other Asset Classes

To represent alternative credit investments, we download historical data on the returns of corporate bonds, government bonds and CDs. This data is publicly available and was downloaded directly from the Federal Reserve Bank of St.Louis database (Fred, 2019).

Corporate Bonds

Bank of America Merill Lynch has created bond indices that show the value of total returns on corporate bonds for the different bond grades. Each index consists of all debt securities within the respective credit rating. The index tracks the performance of publicly issued corporate debt in the U.S. domestic market. All returns are U.S. dollar-denominated. In total, seven indices are downloaded ranging from AAA to CCC. The bond grades AAA, AA, A, and BBB, represent investment grade bonds. While grade BB, B, and CCC show the performance of low-quality bonds or "Junk bonds". The CCC index has aggregated all bond performances in the CCC-C ratings. The average monthly performance from January 2008 to December 2015 is downloaded.

Government Bond

The 3-Year Treasury yield curve is chosen as a representative investment for the government bond asset class. The U.S. government issues bonds with various time to maturities. For consistency in our analysis, the representative government bond is chosen to match the maturity of loans in our dataset. The not-seasonal adjusted monthly yield is downloaded from the beginning of 2008 to the end of 2015. In order to calculate the Sharpe ratios of the different asset classes, the 1-Month Treasury yield is used as a proxy for the risk-free rate. The 1-Month Treasury is chosen as a proxy as it is the most liquid Treasury bond and therefore often considered the best proxy for a risk-free asset (Kane, Marcus, & Bodie, 2014). The average return on the 1-Month T-bill between 2008 and 2015 is 0.22%.

Certificate of Deposit's

The last asset class that we look at are CDs. The OECD has created a data index called the "Certificate of Deposit for the United States" as a part of their Main Economic Indicators release. This index tracks the 90-day yields and rates for CD's in the United States. The yield is downloaded in March 2019, for the same period as our corporate and government bonds.

Moody's

The last source used in our comparison are reports provided by the credit rating agency Moody's. Although Standard and Poor have credit scored a larger amount of bonds, we decide to use Moody's as we find their information to be more clear and give better insights into their credit rating methods. The data from Moody's is collected in March 2019.

At the end of each year, Moody's publishes a report presenting the statistics around bond defaults. They publish them in two reports, one for sovereign bonds and one for corporate bonds. In their Sovereign Default and Recovery Rates, 1983-2016 report, Moody's calculates the cumulative probability for a sovereign government to default on their bonds (Y. Liu, Duggar, & Ou, 2017). We use this report to find the credit risk measure on the U.S. 3-Year Treasury. In particular, we collect the 3-year cumulative probability of default, the Loss Given Default (LGD), and the credit grade. For our analysis of corporate bonds, data was collected from Moody's Corporate Default and Recovery Rates, 1920-2015. This report provids us with a default rate, recovery rate and the credit loss rate for each grade. These grades are represented using an index for each grade of all U.S. corporate bonds.

Additionally, we used Moody's Rating Scale and Definitions report. This report is used to understand how they differentiate between the different risk grades and the methodologies used to measure credit risks (Moody's, 2016). For corporate bonds, analysts take the bond issuers assets, liabilities, past ability to pay loans and other key financial numbers into consideration when deciding on a credit rating. The recovery rate is the value creditors realize at the resolution of a default event (Moody's, 2016). They calculate the credit loss rate as a function of the probability of default and LGD. Unfortunately, Moody's does not provide a recovery rate for each bond grade but only differentiate between loans, senior bonds, and subordinated bonds. Moody's senior bonds are equivalent to AAA-BBB bonds, and the subordinates are equivalent to BBB-C rated bonds.

4.5 Dataset Limitations

Before moving into our analysis, it is important to highlight the limitations of our dataset. First of all, the dataset only contains observations from the seven years between 2008 and 2015. This short period has several limitations. First of all, during these years the American economy has only been through one recession. This limited exposure means we do not have strong evidence on how P2P-loans perform during an economic downturn. In fact, the American economy has been fairly stable during these years. Since 2009, the United States' annual GDP-growth has fluctuated with 50 basis points around 2% (Figure 4). Further, the unemployment rate has steadily decreased without any major fluctuations since the end of the recession in 2009. Additionally, because P2P-lending companies arose in line with the recession, one cannot distinguish between the platform's performance as an emerging business and the recession's effect on its performance. It is therefore hard to determine whether P2P-lending follows credit market trends during a recession.

Another limitation is the imbalanced classification in our dependent variable. Classification imbalance problems arise in machine learning methodologies, such as logit, when the number of positive classifications is far greater than the number of negative classifications. Imbalanced data is a common limitation within loan classifications and credit risk modeling. Historical data shows that in comparison to the numbers of successful loans only a small amount of creditors default on their loans (Federal Reserve, 2019). In the large dataset we collect only 13.9% percent of the loans defaulted. When there is such a large imbalance in the dataset common modeling problems may arise. Machine learning models might classify default loans as fully paid and vice versa. There are two main reasons for this potential result. First, the model may not get optimized results because the model does not get an adequate look at the minority class. Second, it can create problems when creating test samples as obtaining a fair representation of both classes can be difficult. Therefore, to ensure our analysis and findings are not troubled by imbalanced data, we carry out data treatments to re-balance the dataset. We compare the methods of oversampling, undersampling, a combined method and untreated data to analyze whether a class imbalance is a concern for our empirical analysis.

A common problem with large datasets are missing variables. As expressed in our data pre-processing section, several of our observations are not complete. For our purpose, removing the missing observations is the best method for dealing with this limitation. However, there is still potential for the removal of important data. Lastly, the data pre-processing is done manually, and naturally can lead to human errors.

5 Exploratory Data Analysis

After pre-processing the data and performing data cleaning, we start our exploratory data analysis. This is one of the most important steps before building a model in order to detect potential outliers and mistakes.

5.1 Distribution of Interest Rate

An important variable for an investor is the interest rate. In order to inspect the distribution of interest rates we plot a histogram and analyze its summary statistics. Figure 6 shows the distribution of interest rates. The histogram shows that few observations have higher interest rates than 20%. The majority of loans have interest rates between 7% and 15%. Particularly loans with 12%-13% interest rates are frequently issued.

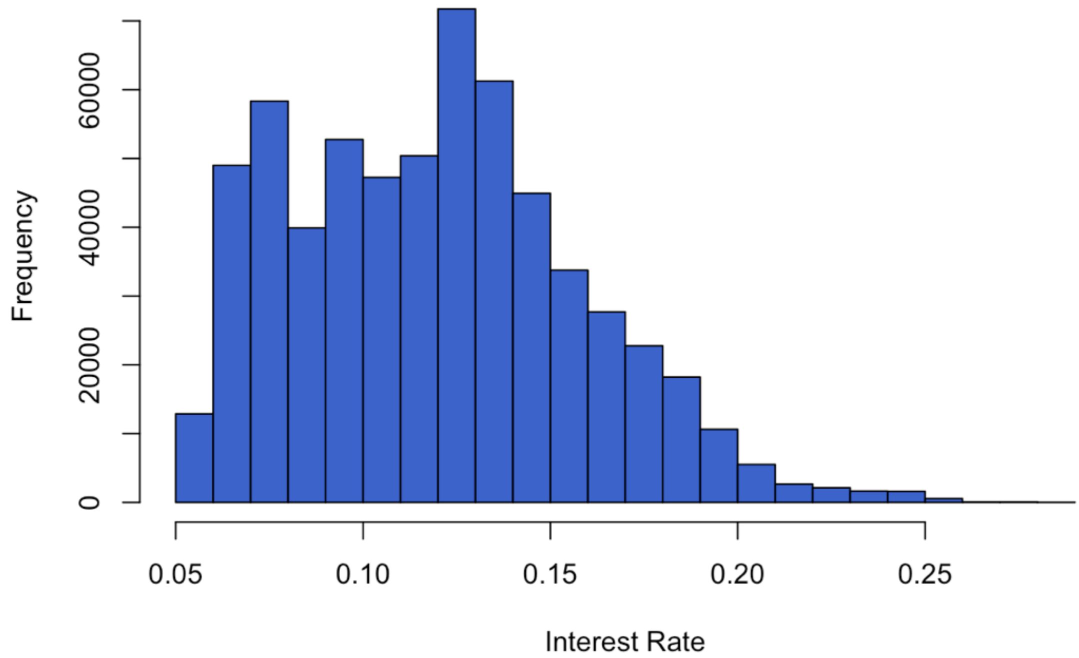

Figure 6: Interest Rate Distribution

Table 1 shows the summary statistics and confirm the observations shown in the histogram. The table shows that 75% of our observations have interest rates lower than 14.5%, and 50% have interest rates between 8.9% and 14.5%. Thus, we get a more detailed look at the distribution. The minimum interest rate is 5.3%, and the maximum interest rate is 29.0%. This maximum interest rate is higher than the rate one would expect on loans from a bank. A reasonable argument for this observation is that LendingClub loans are not secured. Lastly, on average across all grades, an investor can expect an interest rate of 12.0%. A plot showing the increase in interest rate over time is presented in the Appendix (A2.3).

Min	1st Qu.	Median	Mean	3rd Qu.	Max
0.053	0.089	0.120	0.120	0.145	0.290

Table 1: Interest Rate Summary Statistics

5.2 Distribution of Grading Score and Loan Status

Another interesting statistic for an investor is the distribution between credit grades and loan status. This distribution is shown in Table 2. Analysing the percentage of defaulted loans for each grade can provide investors with insight into LendingClub's ability to evaluate risk. As we can see, most of the loans issued are grade B, accounting for almost 34% of the loans. In total, grade A-C loans account for more than 80% of the total loans issued. Moreover, we can see that the proportion of defaulted loans increases for worse credit grades, as expected. Only 5.47% of grade A loans have defaulted, while the percentage of default for the least creditworthy grades, F and G are 32.84% and 38.25%, respectively. However, only a small portion of the total loans are grade F and G. In total they account for 0.8% of the total loans. The negative relationship between default and creditworthiness suggests that LendingClub is properly assigning grades to their borrowers.

	Grades						
Loan Status	**A**	**B**	**C**	**D**	**E**	**F**	**G**
Default	7,756	23,551	28,923	17,730	6,155	1,437	241
	5.47%	11.20%	17.94%	23.34%	28.53%	32.84%	38.25%
Non Default	134,078	186,642	132,321	58,247	15,417	2,939	389
	94.53%	88.80%	82.06%	76.66%	71.47%	67.16%	61.75%
Raw Total	141,834	210,193	161,244	75,977	21,572	4,376	630
	23.00%	34.01%	26.20%	12.30%	3.50%	0.70%	0.10%

Table 2: Loan Status and Grades

5.3 Relationship Between Grade and Interest Rate

To check the validity of our dataset, we examine the relationship between interest rates and grades. Intuitively, better grades should have a lower interest rate, while poorer grades should have higher interest rates. In order to examine this, we compute a scatter plot showing the relationship between sub-grades and interest rates.

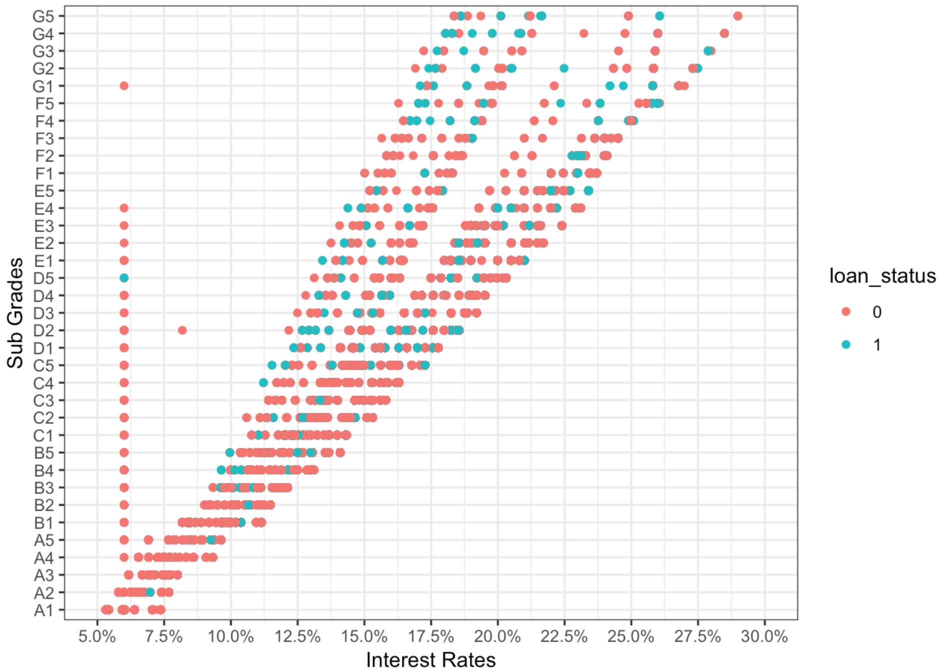

Figure 7: Relationship Between Sub-Grades and Interest Rates

From Figure 7 it is clear that interest rates get higher as the grades get worse. All loans with sub-grades A1-A5 have interest rates below 10%. The scatterplot also confirms that most loans are grade B and C, and only a few loans are grades F-G. The figure also shows that the amount of defaulted loans increases with worse sub-grades. This findings is consistent with the findings in the above paragraph. However, one interesting observation is that almost every sub-grade has one observation with the same interest rate. We look into the dataset to analyze their loan characteristics to see if there are any economic reasons for these observations or whether they are biased outliers. Despite having a significantly lower interest rate than other loans in the same sub-grade, their loan characteristics remain relatively consistent with the rest of their sub-grade. Therefore, there is a strong indication that some form of error has taken place while registering these interest rates. To avoid any bias, these 23 outliers are removed from our dataset.

5.4 Outlier Detection

In machine learning, the quality of data is as essential as the quality of the prediction or classification model. Therefore, detecting outliers is of major importance. Hence, we check the rest of the dataset for outliers using boxplot or scatter plots (see Appendix A2.2). We find several outliers in annual income.

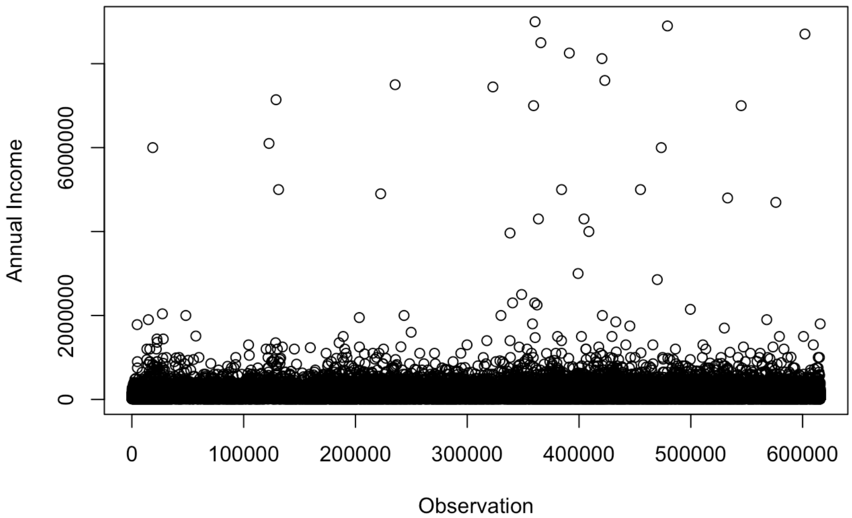

Figure 8: Distribution of Borrower's Annual income

Figure 8 shows the distribution of LendingClub's borrower's annual income. Observing this figure together with the variables summary statistics, shown in Table 3, provides evidence for many outliers. The median annual income in the dataset is $60,000, and the maximum value is $9,000,000. Comparing the maximum value to the third quartile of 87,000, suggests that the highest incomes are extreme cases. Further analysis shows that despite having these extreme incomes, investors are applying for small loan amounts for reasons such as debt consolidation. There is thus strong reasons to believe that some of these extreme values are caused by human error, either by a typo or miss-representation of information. We use our own judgement and remove all observations above $1,000,000. The elimination of annual income observations decreases our data set by 113 observations.

Min	1st Qu.	Median	Mean	3rd Qu.	Max
3,000	43,000	60,000	72,575	87,000	9,000,000

Table 3: Annual Income Summary Statistics

5.5 Multicollinearity

Further, as the final step of our exploratory data analysis, we check the correlation between the variables. This step is important to help us identify variables which are highly correlated and can lead to a multicollinearity problem. Figure 9 shows the correlation matrix for all the numerical variables in our data. From the figure, we can see that *interest rate*, *installment*, *total payment* and *total payment invested* have a correlation of over 0.9 with *loan amount*. Thus, to ensure that all variables are independent of each other and to increase the precision of our models, we keep *loan amount* in our dataset and remove the correlated variables. Moreover, *sub-grade* contains the same information as *grade* only more granular and thus, we exclude it from our model.

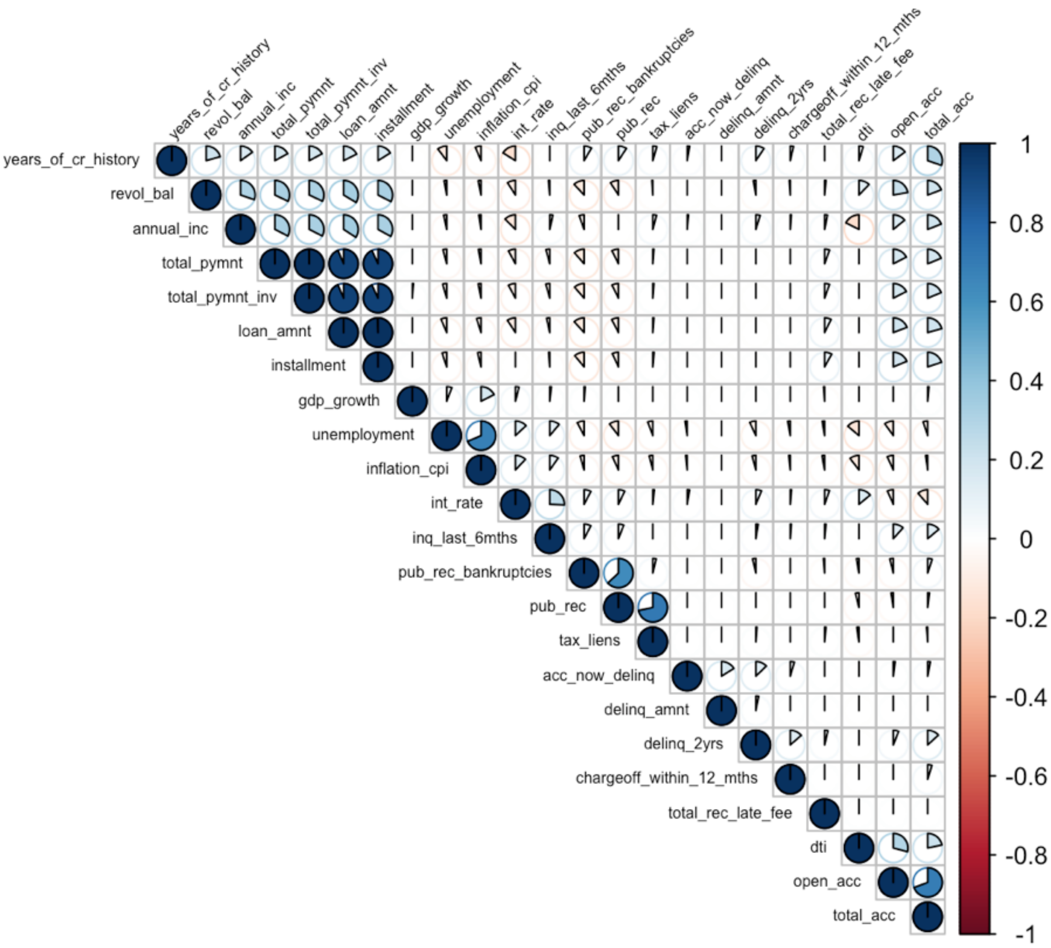

Figure 9: Correlation Matrix of Numerical Variables

The confusion matrix also shows a clear correlation between *CPI* and *unemployment rate*. From macroeconomic theory and specifically the Phillips curve, we know that there is an inverse relationship between inflation and unemployment (Phillips, 1958). As levels of unemployment decrease, inflation increase. Thus, to avoid multicollinearity *CPI* is removed from our model.

5.6 Summary Independent variables

After pre-processing and cleaning the data, our dataset contains 615,573 observations and we are left with our final independent variables. As outlined before, our independent variables consist of socio-economic data, loan characteristics, credit history, and macroeconomic data. Our analysis will attempt to empirically show which independent variables are significant determinants of loan default. Thus, our independent variables are believed to affect the borrower's ability to repay their loans and are selected using financial theories and intuition. Our choice of macroeconomic variables has been discussed and motivated in section 5.2.2. In order to get consistency between the two macroeconomic variables,*unemployment rate* is converted to a growth rate. The unemployment rate variable will from here on be referred to as unemployment growth. In the end, we are left with 22 independent variables of interest. These are be used to specify the best-fitted model to determine loan defaults within our data set. A description of our chosen independent variables is presented in Figure 10.

Variable	Definition
Socio-Economic	
Annual Income	The annual income provided by the borrower during registration
Verification Status	Indicates if income was verified by LC, not verified, or if the income souce was verified
Housing Ownership	Own, rent and mortgage
Employment Lenght	The length of time (in years) that workers have been with their current employer
Debt to Income	Borrower's debt to income ratio. Monthly payments on the total debt obligations. Excluding mortgages, divided by self-reported monthly income.
Loan Characteristics	
Grade	LendingClub categorizes borrowers into seven different loan grades form A down to G, A-grade being the safest
Loan Purpose	14 loan purposes: car, credit card, debt consolidation, educational, home improvement, house, major purchase, medical, moving, renewable energy, small business, vacation, wedding and other
Loan Amount	The listed loan amount applied for by the borrower
Initial list status	The initial listing status of the loan. Possible values are – "F" for fractional, "W" for whole.
Credit History	
Credit History Length	Number of days of credit history considering the date when the borrower's earliest reported credit line was opened
Delinquence 2 years	The number of 30+ days past-due incidence of delinquency in the borrower's credit file for the past 2 years
Inquiries Last 6 Months	The number of inquiries by creditors during the past 6 months
Public Records	Number of derogatory public records
Revolving Utilization	Revolving line utalization rate, or the amount of credit the borrower is using relative to all available revolving credits
Revolving Balance	Total credit revolving balance
Open Accounts	The number of open credit lines in the borrower's credit file
Total Accunts	The total number of credit lines currently in the borrower's credit file
Charged Off within 12 months	Number of charge-offs within 12 months
Tax liens	Number of tax liens
Debt settlement flag	Flags whether or not the borrower, who has charged-off, is working with a debt-settlement company.
Macroeconomic	
Unemployment growth rate	The change in number of unemployed as a percentage of the labour force
GDP growth	The rate at which a nation's GDP changes from one quarter to another.

Figure 10: Description of the models independent variables

6 Theoretical Framework

6.1 Logit Models

To model loan defaults when the dependent variable is binary, classification models are frequently used. A binary dependent variable model will model the probability that an independent variable belongs to a particular classification, commonly $y = 1$. One popular binary classification method is the Linear Probability Model (LPM). In LPM's the independent variables are assumed to be linear in response to a set of parameters β_j. This linearity makes the model popular for its straightforward interpretation and its ability to use OLS (Ordinary Least Squared) estimation. However, there are several disadvantages to using such a method. One of the most vital drawbacks is that fitted probabilities can be less than zero or greater than one. Another important drawback is that the partial effect of any exploratory variable is constant (Woolridge, 2012).

Therefore, using a non-linear response function when predicting loan defaults will limit some of the disadvantages of the LPM. Logit regression is a method used to explore the relationship between a binary dependent variable and continuous or categorical independent variables (Stock & Watson, 2012). The primary goal of a logit model is to formulate a non-linear model that restricts the predicted variables to be between 0 and 1. Logit regressions follow the cumulative standard logistic distribution function. Since the method does not require the independent variables to follow a normal distribution, logistic regression is the recommended procedure when using both continuous and categorical variables (Hanushek & Jackson, 1977). The cumulative standard logistic distribution is close to the standard normal distribution but has thinner tails.

Logistic regression is a linear relationship that performs a non-linear transformation on its output by the use of a sigmoid function. Because of this initial linear relationship, an important underlying assumption for running logistic regressions is that there exists a linear relationship between the independent variables and the dependent variable (Stock & Watson, 2012). The conditional probability of a loan default given our independent variables is:

$$P(y=1|\mathbf{x}) = G(\beta_0 + \boldsymbol{x\beta}) \quad where \quad G(z) = \frac{exp(z)}{1+exp(z)} \tag{1}$$

$$where \quad z = (\beta_0 + \beta_1 x_1 + ... + \beta_k x_k) \tag{2}$$

where β_0 is a constant, $\boldsymbol{\beta}$ is a vector of regression coefficients and $\boldsymbol{x}$ is a vector of independent variables. The sigmoid function, $G(z)$, will take the output of the linear equation, and map any real number, z, to a value between 0 and 1.

The non-linear nature of $G(z)$ makes the interpretation of the individual variable's, x_j, coefficient, β_j, on the probability of $y = 1$ or $P(y = 1|x_j)$ more cumbersome in comparison to OLS. The regression coefficient gives the sign of the partial effects of each x_j and whether the coefficient is statistically significant by testing whether the null-hypothesis, $H0 : \beta_j = 0$ can be rejected. Due to the non-linear nature of a logit model, the magnitude of the effect of x_j, on y is not directly observable. Instead, since x_j is a continuous variable, one can find its marginal effect on y by taking the partial derivative (Woolridge, 2012). The marginal effect shows the effect of an one unit change in x_j on $P(y = 1)$. The partial derivative is given by:

$$\frac{\partial p(\mathbf{x})}{\partial x_j} = g(\beta_0 + \boldsymbol{x\beta})\beta_j \qquad where \quad g(z) = \frac{dG}{dZ}(z) \tag{3}$$

The coefficients of logistic regressions are estimated by Maximum Likelihood (ML). ML allows for estimation of the non-linear relationship between y and x, $E(y|x)$. A favorable characteristic of ML estimators is that they are consistent and normal in large sample sizes. Another benefit of ML estimation is that the heteroscedasticity in the variance, $Var(y|x)$, is already accounted for, since the estimation is based on the distribution of x given y (Woolridge, 2012). This benefit allows for inference using normally constructed t-statistics and confidence intervals. In general, ML and logit regressions overcome many of the assumptions of linear models (Woolridge, 2012). Besides not requiring a heteroscedastic variance or a linear relationship between the dependent and independent variables, logit models do not need normally distributed errors. Despite, having fewer restrictive assumptions, some are still required. Independent variables must be independent of each other and without multicollinearity. Generally, large sample sizes are also preferred. Large sample sizes ensure enough observations of each variable to model a relationship. Lastly, logistic regressions assume a linear relationship between independent variables, as shown in equation 1.

ML estimation chooses parameter values which maximize the probability of drawing the data that is truly observed, by maximizing the likelihood function (Stock & Watson, 2012). The likelihood function, f, is the joint probability distribution of the data, treated as a function of the unknown coefficients. In short, the ML estimators, θ, are the parameter values most likely to have produced the data (Stock & Watson, 2012). The conditional log-likelihood of observation j under ML estimation is shown as:

$$l_j(\theta) = log f(y_j|\mathbf{x_j};\boldsymbol{\theta}) \tag{4}$$

The conditional density function, $f(y|x)$, is a random function since x and y are both random. An assumption of ML estimation is that we know the function of form of f and wish to determine the vector $\boldsymbol{\theta}$.

Unlike linear regressions, R^2 is a poor measure of the model's goodness of fit when using logit models. For binary models, one should instead use alternative goodness-of-fit measures such as the "Pseudo-R^2" or "fraction correctly predicted" (Stock & Watson, 2012). The later states that if the predicted model exceeds 50% and $y = 1$, or if the predicted variable is less than 50% and $y = 0$, then the variable is correctly predicted. To classify the predicted values of each observation into a binary category, a threshold is needed, such as 50% in the below example (Woolridge, 2012).

$$\widetilde{y_j} = 1 \quad if \quad G(\widehat{\beta_0} + x_j\widehat{\boldsymbol{\beta}}) \geq 0.5 \tag{5}$$

$$\widetilde{y_j} = 0 \quad if \quad G(\widehat{\beta_0} + x_j\widehat{\boldsymbol{\beta}}) < 0.5 \tag{6}$$

The percentage correctly predicted is the percentage of times $\widetilde{y_j}= y_j$, where $\widetilde{y_j}$ is the predicted dependent value and y_j is the observed value (Woolridge, 2012). The Akaike Information Criterion (AIC) is a commonly used model selection criteria for logistic and other generalized linear models. The AIC is an estimator for the relative quality of a model given the dataset. It estimates the model's likelihood of predicting unknown or future values. The best model will have the lowest AIC value. AIC is calculated as follows:

$$AIC = 2 * ln(L) + 2 * k \tag{7}$$

where L is the value of the likelihood and k is the number of parameters.

6.2 Classification Accuracy

Logistic regression is a machine learning method from the field of statistics. The goal is to find a well-specified model that accurately predicts the probability of the dependent variable belonging to a given class. Deciding which model performs the best on a given dataset is not always straight forward and can be a real challenge for some studies. In order to determine the optimal model, some statistical measures allow us to easily evaluate models against each other. When determining the best model, these measures should not be evaluated individually but complementary.

The predictive accuracy of a model is based on the difference between the observed values and the predicted values. A true positive (TP) is a positive observation that is correctly classified as a positive observation. On the other hand, a false positive (FP) is a negative observation that is wrongly classified as a positive observation. The same logic follows for true negatives (TN) and false negatives (FN). A false negative is the same as a Type II error in the field of statistics, and a false positive is the same as a Type I error (Labatut & Cherifi, 2012). The four possible classification outcomes can be summarized by a confusion matrix.

		Predicted	
		Negative	Positive
Actual	Negative	TN	FP
	Positive	FN	TP

Table 4: Confusion Matrix

The confusion matrix is a widely applicable table and many performance measures are derived from it. Accuracy, measures the overall ratio of correctly predicted observations and can give an overall view of the models performance. However, it does not perform well on imbalanced datasets, since miss-classifying the minority class will lead to high accuracies.

$$Accuracy = \frac{TN + TP}{N + P} \tag{8}$$

In order to get a clearer picture of the prediction strengths and weaknesses of a model, it is helpful to look at sensitivity and specificity measures (Labatut & Cherifi, 2012). In particular these can determine whether the accuracy is miss-guiding. Sensitivity is also known as recall and shows how well the model correctly classifies true positives.

$$Sensitivity = \frac{TP}{TP + FN} \tag{9}$$

Specificity corresponds to the proportion of observations correctly predicted to belong to the negative class.

$$Specificity = \frac{TN}{TN + FP} \tag{10}$$

An alternative method to evaluate a models classification capabilities is to use the Receiver Operating Curve (ROC) and the Area Under the ROC Curve (AUC). The ROC is a parametric plot of sensitivities against the false alarm rate at a full range of threshold settings (Marzban, 2004). The false alarm rate is the same as $1 - specificity$.

$$AUC = \int_{x=0}^{1} sensitivity((1 - specificity)(x))^{-1} dx \tag{11}$$

By using the AUC, one can consider all possible thresholds, resulting in different sensitivity and specificity measures. The optimal threshold can therefore easily be detected. An AUC of approximately 0.5 indicates the worst performance of a model and shows that the model has no predictive power to distinguish between the positive and the negative class (Narkhede, 2018).

6.3 Expected Return and Investor Behaviour

Evaluating investment decisions using expected returns is a widely studied area in financial literature. One intention for studying the demand for assets is to establish an investor's preferences over different uncertain returns. A popular measure for the attractiveness of an asset is by the average or expected payoff of an asset (Pennacchi, 2007). The expected payoff is expressed as:

$$\overline{x} = E[\widetilde{x}] = \sum_{i=1}^{n} p_i x_i \tag{12}$$

An investor is expected to choose the investment opportunity with the highest expected return. Although it is a popular measure, the expected payoff has historically not captured the behaviors of investors well. Therefore, economists have developed several theories to explain the diversion between the expected and the observed behaviors, such as the expected utility theories and the prospect theory. The famed St.Petersburg Paradox [2] first brought light to the major shortcomings of solely using expected payoff when making investment decisions (Joyce, 2011). Instead, the concept that individuals care about the utility they get from their investments and not the direct value of their payoffs was introduced.

$$E[U(\widetilde{x})] = \sum_{i=1}^{n} p_i U, \quad where \quad U(\widetilde{x}) = p_1 U(x_1) + ... + p_i U(x_i) \tag{13}$$

Equation 13 shows an investor's expected utility as a function of the utility received from the payoff of their investment choices, $U(x_i)$. Further, findings from the paradox imply that investors have concave utility functions and marginally decreasing utilities. This indicates that investors are risk averse (Pennacchi, 2007). Moreover, this suggests that investors prefer a lower certain payoff, than a higher uncertain payoff. Thus, investors may choose investment alternatives with lower expected values. Behavioral economist call this phenomenon the certainty effect, and is a part of the prospect theory (Ackert & Deaves, 2010). In addition to being risk averse in choices involving sure gains, investors also tend to be risk seeking in choices ensuring sure losses (Kahneman & Tversky, 1979).

[2] For more information see: Samuelson (1977) and Joyce (2011)

There is an abundance of additional evidence that justifies that under most circumstances investors are risk averse (Ackert & Deaves, 2010). Further studies have emphasized that a rational investor will always choose an investment option that efficiently pays a higher expected return for a lower or equal variance of return (Ackert & Deaves, 2010).

The presence of risk premiums in asset markets builds on the ideas of expected utility and risk aversion. On the one hand, the risk premium can be viewed as the price the investor pays in order to avoid risk (Pratt, 1964). On the other hand, the risk premium is motivated as the expected rate of return above the risk-free rate (Arrow, 1971). The risk premium is positively related to the level of risk in order to compensate investors for the risk they hold.

Thus, when analyzing the expected payoff of an investment option, it is important to consider the measures limitations as well as, the relationship between expected return, the investor's behavior, and risk aversion. Keeping in mind an investor's characteristics when evaluating P2P-lending with other asset classes might provide further insight into which type of investors P2P-lending is attracting.

6.4 Sharpe Ratio

Investing in P2P-lending has its risks. Therefore, it is important for investors to understand whether the returns offered by their investment are worth the underlying risks. In 1966, William Sharpe introduced the expected excess return per unit of risk as a measure of investment performance (Sharpe, 1966). The Sharpe ratio has become one of the most popular measures of risk-adjusted return on investments. The key purpose of the Sharpe ratio is to evaluate the total performance of an investment considering the investment's risk exposure. More specifically, the ratio indicates how well an investment performs in comparison to the rate of return on a risk-free investment. All else constant, a higher Sharpe ratio is favored. The formula for calculating the Sharpe ratio is defined as follows:

$$Sharpe\,Ratio_p = \frac{E(r_p) - r_f}{\sigma_p} \tag{14}$$

where r_p is the return of the investment p, r_f is the corresponding risk-free rate, and σ_p is the standard deviance. Two of the components of the Sharpe ratio - expected return and the standard deviation - are unknown measures that must be estimated statistically. The standard deviation of an investment represents the volatility of the investment's return and proxies the risk of the investment. In order to compensate for the higher standard deviation, the investment needs to generate a higher return to maintain a higher Sharpe ratio.

In other words, calculating the Sharpe ratio on P2P-lending investments allows for a direct comparison to other investment opportunities. However, the Sharpe ratio has several shortcomings. First of all, several researchers argue that the Sharpe ratio is subject to estimation errors due to its two unknown variables (Kourtis, 2016; Lo, 2002). Bodnar and Zabolotskyy (2017) emphasize that the standard deviation can, in particular, be a problematic measure of risk. They show that high returns increase the standard deviation, and thus, also the variance. Further, they suggest that better risk measures use the probability or value of losses. Second, the Sharpe ratio may not give a reliable comparison if there is a correlation between one or more of the assets and the rest of the portfolio (Sharpe, 1994). If asset A has a higher Sharpe ratio than asset B, but the expected return on A is positively correlated with the rest of the portfolio and B is negatively correlated, then purchase of asset B would reduce portfolio risk. This example implies that investment decisions can be too complex for just the Sharpe ratio (Dowd, 2000). It is, therefore, important to not make an investment decision based solely on the Sharpe ratio.

6.5 Bond Theories

Corporate and government bonds are two popular credit market investments. A benefit of investing in bonds over P2P-loans are the established theories explaining bond behaviors and structures. The bond structure closest to a P2P-loan is the fixed-coupon bonds. A fixed coupon bond pays a fixed coupon at regular intervals until the bond reaches maturity. At maturity debtors pay investors the bond's principal (Cochrane, 2005). A bonds theoretical price can be calculated as the present value of all cash flows received by the owner of the bond (Hull, 2012). The bonds price is written as:

$$P_i = \sum_{t=1}^{T} \frac{Coupon}{(1+r)^t} + \frac{Principal}{(1+r)^T} \tag{15}$$

T represents the bonds maturity date, r is the interest rate, and t is the time-period. Most bonds do not sell at par value, but dependent on no default, will mature at par value (Kane et al., 2014). The return of the bond is determined by several characteristics: the price of the bond, time to maturity and the coupon rate. The bond's yield is often used by investors to calculate the bond's return. The yield for a given bond price can be found using equation 15 and solving for the interest rate. Thus, there is a negative relationship between the bond yield and the bond price. Further, the yield of a bond can be viewed as the interest rate that explains the market price of the bond (Cochrane, 2005).

Additionally, the bond market has a negative relationship with the interest rate. When interest rates rise, the opportunity cost of holding a bond increases causing the bond's price to fall and the bond sells at a discount. The opposite follows for decreases in interest rates. Bonds then sell at a premium (Kane et al., 2014). The decrease in price occurs because the fixed coupons cannot compensate for the higher interest rates (Jordan & Sundaresan, 2009). As a result, the bond is worth less than the price paid for it and the yield decreases. Thus, one can see how bond performances are directly related to macroeconomic factors and monetary policies.

These changes in interest rate risk have more significant impacts on bonds with longer times to maturities. This is because bonds with greater times to maturities are more sensitive to price fluctuations related to changes in the interest rate (Kane et al., 2014). This rationale also acknowledges that bonds with the shortest maturities are the least risky. Again, this is proved by looking at the relationship between the variables in equation 15.

7 Methodology

The methodology is designed to address our research question of whether P2P-lending is a relevant asset class for investors. A natural way to approach this research question is to compare the expected returns in P2P-lending to other investment opportunities. In order to answer the research question feasibly, the methodology is divided into four parts. The first thing we need to do is find the risks associated with P2P-lending. Since loan default is considered to be the biggest risk regarding P2P-loans, Part I of our methodology intends to find the determinants of loan default. Considering that macroeconomic conditions play a significant role in the performance of traditional investment opportunities, we want to exclude that the macroeconomic condition of the economy is an omitted variable in the performance of P2P-loans. Hence, Part II includes macroeconomic variables in the model. Part III calculates the expected return that a lender should forsee from a P2P-loan investment. Further, Part III also takes the Sharpe ratio as a basis for comparison between the different investment alternatives. Lastly, Part IV compares the risk classification of LendingClub's credit grades to those provided by Moodys.

7.1 Part I - Determinants of Default

The determinants of loan defaults are analyzed using logistic regression methods. The first step of building a logistic regression model is to split the data into a training and a testing set. By doing so, the model is first optimized on the training set. Afterward, the parameters of the model are run on the testing set to ensure the model is fitting. This last step validates the model and detects over-fitting. 70% of the data is used to train the model, and 30% is used to test it. The two datasets are drawn randomly to guard the sample from bias (Panzeri, Magri, & Carraro, 2010).

To ensure our results are not impaired by errors arising from an imbalanced dataset, we re-balance the data. Four re-balancing methods are carried out: oversampling, under-sampling, doing both and the R-function ROSE. The Random Over-Sampling Exampling (ROSE) function produces a synthetic and balanced dataset by using a smoothed boot-strap approach (Tantithamthavorn, Hassan, & Matsumoto, 2018). Undersampling and oversampling the data are two opposing approached to balance data. When undersampling the data one deletes random observations from the majority class in order to match the number of observations in the minority class. Oversampling, on the other hand, generates random, artificial data to sample the characteristics of the minority class (Badr, 2019). The last approach balances the data by combining the methods of undersampling and oversampling (Tantithamthavorn et al., 2018).

In order to find the best-fitted model, we use several methods for finding model specifications. Namely, Lasso regressions, stepwise selection using AIC, F-tests and standard t-tests are compared. These approaches are performed independently. The Lasso (Least Absolute Shrinkage and Selection Operator) is a powerful feature selection technique. It is a regularization method that reduces overfitting by removing less important variables, after checking that they are not important for the model. The other regularization method used is stepwise selection. Equivalent to the Lasso method it attempts to remove any insignificant variables from the model. To ensure that we have the best-fitted model, we run the stepwise selection AIC both ways. Running both ways means the function begins with a null or full model and tests the addition or deletion of each variable using a chosen criterion. The model then adds (deletes) the variable whose inclusion (loss) gives the most statistically significant (insignificant) improvement of the model. The last approach is checking the significance of the independent variables using the F and t-test statistics and is a standard approach to finding a correctly specified model. As our base model and starting point, we use the following logistic model:

$$\begin{aligned}
&LoanStatus = \alpha + \beta_1 loan.amnt + \beta_2 grade + \beta_3 home.ownership + \beta_4 annual.inc \\
&+ \beta_5 verification.status + \beta_6 purpose + \beta_7 dti + \beta_8 delinq.2yrs + \beta_9 years.of.credit.history \\
&+ \beta_{10} inq.last.6mths + \beta_{11} open.acc + \beta_{12} pub.rec + \beta_{13} revol.bal + \beta_{14} total.acc \\
&+ \beta_{15} initial.list.status + \beta_{16} acc.now.delinq + \beta_{17} chargeoff.within.12.mths \\
&+ \beta_{18} delinq.amnt + \beta_{19} tax.liens + \beta_{20} debt.settlement.flag + \beta_{21} emp.length + \epsilon
\end{aligned} \tag{16}$$

Six of the variables in the above equation are categorical. Since logistic regression models require numerical inputs, the model converts each categorical variable into a numeric variable by employing dummy variables. After creating dummy variables for each category, we are left with 42 variables in our model.

The base regression is first run on the training set of each of the four balanced datasets and the imbalanced dataset. For the standard test statistics approach significant variables at the 5% level are removed. The models are then re-run without the insignificant variables to see whether the exclusion of insignificant variables improved the models fit.

The next step after fitting the models is to see how the models perform when predicting *Loan Status* on a new dataset. Cross-validating the models on our test data is a method to check the models' robustness. Across data samples and specification methods we have in total of 15 models to compare.

There are several criteria to consider when determining which model best fits the data. The performance of each model is compared using the performance measures outlined in our Theoretical Framework. Because we are performing analysis from the perspective of an investor who is mainly concerned about the credit risk of their investments, we argue that it is more important to find a model that is strong at correctly predicting defaulted loans, and it is less critical that the model falsely predicts non-defaulted loans as defaulted. Therefore, when analyzing the different models, we place greater emphasis on the ROC curve and the sensitivity of our models, than on the accuracy.

The comparative results and motivation for our model choice is provided as a part of our findings. The final regression model of Part I, Model 1, is defined as follows:

$$
\begin{aligned}
&LoanStatus = \alpha + \beta_1 loan.amnt + \beta_2 grade + \beta_3 home.ownership + \beta_4 annual.inc \\
&+ \beta_5 verification.satus + \beta_6 purpose + \beta_7 dti + \beta_8 delinq.2yrs + \beta_9 years.of.credit.history \\
&+ \beta_{10} inq.last.6mths + \beta_{11} open.acc + \beta_{12} pub.rec + \beta_{13} revol.bal + \beta_{14} total.acc \\
&+ \beta_{15} initial.list.status + \beta_{16} acc.now.delinq + \beta_{17} delinq.amnt + \beta_{18} tax.liens \\
&+ \beta_{19} emp.length + \epsilon
\end{aligned}
\tag{17}
$$

To gain further understanding of which variables determine default we analyze the variable importance of each independent variables in Model 1. This is done by evaluating the absolute value of the t-statistic for each coefficient.

$$t_{\widehat{\beta}} = \left| \frac{\widehat{\beta_1} - \beta_0}{se(\widehat{\beta_1})} \right| \tag{18}$$

These measures do not quantify the effect of the coefficient on the dependent variable but give an aggregate measure of each independent variable's impact on the dependent variable.

7.2 Part II - Including Macroeconomic Variables

Part II tests whether the structural form of Model 1 is correct. In particular, we test whether the macroeconomic condition's at the time of loan issue is an omitted variable. To represent the macroeconomic condition of the U.S., we add two variables, *unemployment growth*, and *GDP growth*. Regression Model 2 is defined as follow:

$$\begin{aligned}
&LoanStatus = \alpha + \beta_1 loan.amnt + \beta_2 grade + \beta_3 home.ownership + \beta_4 annual.inc \\
&+ \beta_5 verification.satus + \beta_6 purpose + \beta_7 dti + \beta_8 delinq.2yrs + \beta_9 years.of.credit.history \\
&+ \beta_{10} inq.last.6mths + \beta_{11} open.acc + \beta_{12} pub.rec + \beta_{13} revol.bal + \beta_{14} total.acc \\
&+ \beta_{15} initial.list.status + \beta_{16} acc.now.delinq + \beta_{17} delinq.amnt + \beta_{18} tax.liens \\
&+ \beta_{19} emp.length + \beta_{20} unemployment.growth + \beta_{21} gdp.growth + \epsilon
\end{aligned} \tag{19}$$

The best-fitted model is found using the same model specification methods as in Part I. Specifically, Lasso, stepwise selection, and significance testing using F-test and t-test. The next stage is to evaluate the models' performance. To be consistent with our previous method the same evaluation methods are used, placing greater emphasis on the measures important to an investor.

We perform a likelihood ratio test to see whether Model 2 performs better than Model 1. The likelihood ratio test compares the fit of one model with the fit of another model to test whether there is a significant difference between the two nested models. Model 1 is a nested model of Model 2 and is our restricted model. The null hypothesis is $H_o : k_r = k_{ur}$, where k is the number of parameters in each model. Rejecting the null hypothesis would mean the unrestricted model fits the data better. The LR statistic follows the chi-squared distribution and is constructed as:

$$LR = 2(L_{ur} - L_r) \tag{20}$$

Where L_{ur} is the log likelihood of our unrestricted Model 2 and L_r is the log likelihood of the restricted Model 1. The degrees of freedom is equal to the number of parameters that are restricted, which in this case is 2 (Woolridge, 2012).

7.3 Part III - Expected Return and Sharpe Ratio

The final step of our analysis aims to compare investing in LendingClub's grade classes to the different grade classes of corporate bonds and government bonds. As well as investing in CDs. Hence, the research will not address diversification strategies but solely focus on investment within each grade class.

To calculate the expected return of a loan in LendingClub, we analyze the data as consisting of seven portfolios determined by their grade. Where portfolio A consists of loans of grade A and portfolio B of grade B loans etc. Although LendingClub's notes sell in a secondary market, we assume that investors hold their loan positions until maturity. We also assume that the investor does not re-invest money received from installments, early payments or defaults. This assumption allows us to ignore the time value of money and compounding effects.

The expected return for every loan is obtained by using the following equation:

$$E[r_i] = \frac{Total\,Payment_i}{Total\,Funded\,Amount_i} - 1 \tag{21}$$

where $Total\,Payment_i$ is the total dollar amount an investor has been paid back on an invested loan i. For non-defaulted loans, this will be the sum of all installments and any applicable late fees. An investor of a defaulted loan will have a total payment equal to the sum of all installments received before defaulting and any recovery amount. $Total\,Funded\,Amount_i$ is the total funded amount or the dollar amount of a loan funded by an investor.

The expected return on a portfolio is calculated as the arithmetic mean of the expected return of each loan:

$$E[r_p] = \frac{1}{n}\sum_{i=1}^{n} E[r_i] \tag{22}$$

where n is the total number of loans and r_i is the loans interest rate. The standard deviation of the portfolio of loans is calculated as:

$$\sigma_p = \sqrt{\frac{\sum_{n}^{i=1}(r_i - E[r_p])}{n-1}} \tag{23}$$

The sources of volatility vary for the different credit market assets. While credit risk is a common concern for all investors, bond market investors must also account for interest rate risk and degrade risk. Commercial depositors are also exposed to interest rate risk. If the interest decreases investors get a lower return on their investments. In comparison, LendingClub's interest rates and grades are fixed for the duration of their loans. Therefore, we focus on calculating credit risk. There are several ways to measure credit risk. Two measures to express credit risk are LGD and the Credit Loss Rate. These measures are constructed as:

$$LGD = (1 - \frac{Expected\ Time\ to\ Default}{Time\ To\ Maturity}) \tag{24}$$

$$Credit\ Loss\ Rate = LGD * P(D = 1) \tag{25}$$

Although the expected return gives an indication of the returns an investor can expect when investing in a given portfolio, it is a basic measure and does not account for the volatility of these returns. To measure return adjusted for volatility, we have calculated the Sharpe ratio for each grade portfolio.

As presented in our Theoretical Framework the Sharpe ratio consists of three variables: the expected return of the portfolio, the standard deviation of the portfolio, and the risk-free rate. The first two variables are calculated using equation 22 and 23, respectively. The choice of using the 1-Month Treasury-bill as the risk-free rate was motivated in section 4.4.

7.4 Part IV - Comparing Credit Grades

Credit grades are common to both bonds and LendingClub loans. These credit grades range from least risky to most risky and are represented by some letter combination where A grades are the most creditworthy. Part IV compares the difference in riskiness between grades in LendingClub and corporate bonds. The calculated Sharpe ratios, the expected returns, and the probabilities of default for all asset classes function as the base for this comparison. Further, this comparison will be used to translate LendingClub's credit grade system to a more recognized grading system. The findings from this stage will give investors a better understanding between the risk levels of each grade and the overall risk level of P2P-lending.

8 Main Findings and Analysis

8.1 Part I - Determining Default

The first part of our empirical analysis is to evaluate loan defaults on LendingClub's platform. An investor is mostly concerned with whether a borrower will default on their loan or not. Knowing which variables are significantly related to loan defaults can help an investor evaluate their investment options and pick loans less likely to default. Further, predicting the default rate of LendingClub loans can also provide investors with risk management guidance. This part provides a brief discussion on the evaluation of the different models, followed by a detailed presentation of the findings from Model 1. The main analysis is done by looking at the estimated parameters of the logistic regression Model 1 and the ranking of each variable's importance. We also discuss the model's prediction performance and its goodness of fit.

8.1.1 Evaluation of Models

The results from running the base model (eq. 16) show that Lasso, stepwise selection, and the combined use of t-tests and F-tests, lead to the same specified model for the undersampled, oversampled, the combined over and undersampled and the imbalanced datasets. The dataset generated by the ROSE package is the only one who has differing outcomes and removes two additional variables.

A quick observation from comparing the models is that the models on average do not perform particularly well. Table 5 provides the most important estimations from the performance measures of each model. The accuracy of the models range between 0.607 and 0.876. The AUC's ranged between 0.614 to 0.861 for Lasso and were about 0.676 for stepwise selection. Meaning that our models are far from perfect but provide stronger predictions on loan default, than a blind guess (a blind guess is equivalent to AUC=0.5). The AUC's also suggest that the stepwise model is a better prediction model. To analyze our models' performance further, we look at the confusion matrix (see Appendix A3.1.2) together with the sensitivity and specificity measures of each model. Interestingly, despite removing two additional variables, the model run using the ROSE method does not perform better or worse than the models using different balancing methods. Indeed, the only models whose performance measures differs from the rest were the two models run on the original imbalanced dataset. Although the two models have higher accuracies than the other models, the true positive rates, represented by sensitivity, are low. In other words, balancing the data improves the logistic regressions and its ability to classify defaulted loans correctly. Both Lasso and stepwise selection choose the same model specification. However, the model from stepwise selection is found to perform the best after comparing the performance measures.

Thus, we decide to continue forward using a balanced dataset. Since there is no statistically significant difference between the stepwise selection models in terms of their precision accuracy and fit, it is arbitrary which model is used to determine loan defaults. The rest of the empirical study uses the undersampled model as it performs negligible better in regards to the sensitivity, and does not seem to be harmed by any loss of information. The chosen model is highlighted in Table 5. The accuracy of our chosen model is in line with other studies (Serrano-Cinca et al., 2015).

	Lasso				**Stepwise Selection**			
	Accuracy	*Sensitivity*	*Specificity*	*AUC*	*Accuracy*	*Sensitivity*	*Specificity*	*AUC*
imbalanced	0.876	0.111	0.999	0.861	0.861	0.001	0.999	0.676
Undersampled	0.657	0.641	0.660	0.619	0.607	0.661	0.598	0.676
Oversampled	0.659	0.640	0.662	0.615	0.609	0.660	0.601	0.676
Both	0.660	0.639	0.662	0.616	0.609	0.659	0.602	0.676
Rose	0.661	0.639	0.665	0.614	0.611	0.656	0.604	0.675

Table 5: Performance Measures of Model Specifications

8.1.2 Regression Results

The regression output of Model 1 is presented in Table 6. The first column shows the estimates of the regression parameters. As explained in the Theoretical Framework, these coefficients give the sign of the effect but are beyond that, not easily interpreted. Thus, the marginal effect and its standard errors are given in the second and third column, respectively. The fourth column presents the p-value. All values in Table 6 are rounded to the nearest hundredth (see Appendix A3.1.4 and A3.1.5 for full values). Lastly, the significant variables are indicated by their significance level, where *** are significant at the *** 0.1% level, ** at the 1% level and * at the 5% level. These representations are used throughout the thesis. The results in Table 6 exhibit that 27 out of 42 variables are highly significant.

Our model finds *grade* to be highly significant and that the probability of default increases as the borrower's grade worsens. This finding is consistent with the analysis from the Exploratory Data section. Figure 11 shows the 15 most important variables as determined by the t-test in equation 18. The grades C, D, E, and F, are among the variables that have the most substantial impact on our model and thus also on the probability of default. This result is also seen in the marginal effects shown in Table 6, as the marginal effect increases as the borrower's grade worsen. The marginal effect gradually increases from 0.17 for grade B to 0.38 for grade G. Thus investors gain significant insight into the creditworthiness of borrowers by looking at their grade. The majority of the presented literature supports this finding. However, the result contradicts with Tao et al. (2017), who found grade not to be a good representation of the borrower creditworthiness.

Loan amount is another variable found to be highly significant in predicting loan default. The positive coefficient implies that borrowers with large loans are more likely to default. All else equal, this shows that borrowers who request large loan amounts and therefore have larger installments are less likely to be able to repay their loans.

	Loan Status				
Predictors	*Estimate*	*df/dx*	*Std.Err*	*p*	
(Intercept)	-1.43	-	-	**<0.001**	***
loan_amnt	0.00	0.00	(0.00)	**<0.001**	***
grade B	0.67	0.17	(0.00)	**<0.001**	***
grade C	1.13	0.27	(0.00)	**<0.001**	***
grade D	1.41	0.32	(0.00)	**<0.001**	***
grade E	1.62	0.34	(0.01)	**<0.001**	***
grade F	1.82	0.36	(0.01)	**<0.001**	***
grade G	2.00	0.38	(0.02)	**<0.001**	***
home_ownership Own	1.15	0.04	(0.01)	**<0.001**	***
home_ownership Rent	0.27	0.07	(0.00)	**<0.001**	***
annual_inc	-0.00	-0.00	(0.00)	**<0.001**	***
verification_status Source Verified	0.11	0.03	(0.00)	**<0.001**	***
verification_status Verified	0.06	0.02	(0.00)	**<0.001**	***
purpose credit card	-0.02	-0.00	(0.02)	0.754	
purpose debt consolidation	0.04	0.01	(0.02)	0.563	
purpose educational	0.51	0.13	(0.06)	**<0.049**	*
purpose home improvement	0.05	0.01	(0.02)	0.416	
purpose house	0.08	0.01	(0.03)	0.438	
purpose major purchase	-0.02	-0.00	(0.02)	0.805	
purpose medical	0.09	0.02	(0.02)	0.261	
purpose moving	0.07	0.02	(0.02)	0.411	
purpose other	-0.06	-0.02	(0.02)	0.341	
purpose renewable energy	0.20	0.05	(0.05)	0.338	
purpose small business	0.41	0.10	(0.02)	**<0.001**	***
purpose vacation	0.05	0.01	(0.02)	0.584	
purpose wedding	-0.19	-0.05	(0.03)	0.156	
dti	0.02	0.00	(0.00)	**<0.001**	***
delinq_2yrs	0.05	0.01	(0.00)	**<0.001**	***
years_of_cr_history	-0.00	-0.00	(0.00)	**<0.001**	***
inq_last_6mths	0.10	0.02	(0.00)	**<0.001**	***
open_acc	0.02	0.00	(0.00)	**<0.001**	***
pub_rec	0.09	0.02	(0.00)	**<0.001**	***
revol_bal	-0.00	-0.00	(0.00)	**<0.001**	***
total_acc	-0.00	-0.00	(0.00)	**<0.001**	***
initial_list_statusw	0.07	0.00	(0.00)	0.169	
acc_now_delinq	-0.07	-0.02	(0.02)	0.399	
delinq_amnt	0.00	0.00	(0.00)	0.778	
tax_liens	-0.05	-0.01	(0.01)	**<0.026**	*
emp_length1-3	-0.06	-0.02	(0.01)	**<0.011**	*
emp_length 10+	-0.05	-0.01	(0.01)	**<0.045**	*
emp_length 4-6	-0.05	-0.01	(0.01)	0.066	
emp_length 7-9	-0.03	-0.01	(0.01)	0.296	
emp_length missing	0.39	0.10	(0.01)	**<0.001**	***

Table 6: Regression Output Model 1

Further, *annual income* and *dti* are both highly significant variables. In line with expectations, the positive sign of *dti* shows that borrowers with higher amounts of debt have greater difficulty repaying their loans. Figure 11 shows that along with *grades*, *dti* is one of the variables with the largest impact on our model and serves as another indicator of the borrowers' riskiness. On the other hand, *annual income* has the opposite effect on default and is negatively correlated with *dti*, indicating that borrowers with higher income and more liquidity are less likely to default.

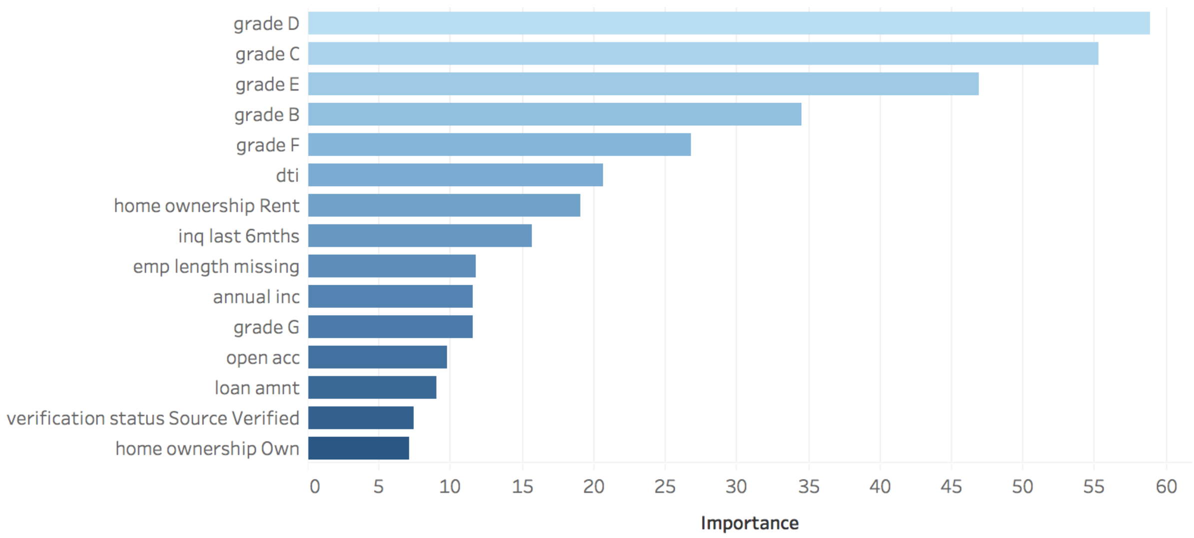

Figure 11: Variable Importance From Model 1

The results in Table 6 shows that all credit history variables are highly significant. Aligned with our expectations, *Delinquency 2 years*, *inquires last six months* and *public records*, all reflect the borrowers lack of payment credibility and increase the probability of default. In contradiction, both high *revolving balance* and *total accounts* signal the availability of alternative capital sources for the borrower. This source of capital can be used to pay loan installments in case of liquidity difficulties. As a result, these variables bring down both the associated risk level and the interest rate, and have a negative relationship with default.

Out of the 14 dummy variables representing loan purposes, only small business and education are significant. Our results suggest that borrowers needing a loan to help finance their education are riskier borrowers than those borrowing for purposes such as consolidating their debts, financing their vacations or weddings. Assuming borrowers fund their own education this result is reasonable as the borrowers are likely to be either unemployed or part-time workers. Consequently, this makes the repayment of loan payments difficult and costly. These results are in agreement with findings from other credit markets (Dynarski, 2015). Behind grades and education, small business has the highest marginal effect. Borrowers who need financing for small business are thus found to be highly risky. This result is consistent with our analysis of default rates within each purpose, where small business loans were found to have the highest default rate amongst purposes (see Appendix A2.1). Further, these results are consistent with Conlin (1999) who found that entrepreneurs experience difficulties getting their loans funded because they are perceived as high risk.

It might come to a surprise for those new to LendingClub that they do not have a standard verification process. In fact, some of their borrowers have not had their self-provided information verified at all. Table 6 shows that both the dummy variables for *verification status* are significant. However, their marginal effects on loan default differ. Those who have their sources verified are more likely to default than those who have their information completely confirmed. Not intuitive, however, is that these loans have a higher probability of default than those borrowers who have not been verified in any way. Although there lacks economic intuition to support this finding, it is consistent with Askira Gelman (2013)'s empirical analysis on LendingClub. One explanation for this result could be that LendingClub verifies the borrowers they believe to have a higher risk of default.

The borrower's employment length is included in our regression as a dummy variable. The regression results in Table 6 show that the marginal effect on loan default is 0.10, when the borrower is unemployed as shown by the variable *emp_length missing*. Although other employment lengths are also highly significant, none have nearly as great of an impact on the likelihood of default. This result substantiates the relationship between income and default.

8.2 Part II - Including Macroeconomic variables

The second part of our analysis looks at macroeconomic variables and their significance in determining loan default. For this part, we apply Model 2 which includes *unemployment growth* and *GDP growth* as variables to represent the economic condition of the U.S. at the time of issue. Again stepwise selection, Lasso and significance testing resulted in the same model specification.

	Lasso				**Stepwise**			
	Accuracy	*Sensitivity*	*Specificity*	*AUC*	*Accuracy*	*Sensitivity*	*Specificity*	*AUC*
Model 2	0.658	0.640	0.661	0.629	0.608	0.661	0.599	0.677

Table 7: Performance Measures For Model 2

Table 7 shows that the AUC is 0.629 for the Lasso model and 0.677 for the stepwise selection method. Again, stepwise selection proves to be the best model specification. Further, Table 7 shows that the predictive power of Model 2 did not improve from Model 1. However, it does not decrease its predictive power either. The AUC's are slightly improve in Model 2, indicating that Model 2 is better at predicting true positives and true negatives. Although the sensitivity of Model 2 remains the same as in Model 1, the higher AUC is a result of the increase in specificity from 0.598 in Model 1 to 0.599 in Model 2. Furthermore, the increase in AUC implies that including the macroeconomic variables makes the model more robust as the variables can capture more signals from the data. The Pseudo-R^2 statistic for Model 2 remained low, but is slightly higher then Model 1 showing a direct improvement in the goodness of fit of our model (see Appendix A3.3).

To further compare the models, we perform a LR test to see whether there is a significant difference between the models. The χ^2 from the LR test is 40.407 with 2 degrees of freedom and we conclude at a high significance level that there is a statistical difference between the unrestricted Model 2, and the restricted Model 1. Thus, Model 2 is a better-fit model (see Appendix A3.3).

Table 8 provides an extraction of the regression output from Model 2. The table only presents the macroeconomic variables as the other variables where similar to the estimates from Model 1. The rest of the regression results are found in Appendix (A3.2.1). The results show that *GDP growth* has a negative effect on the probability of default. However, *GDP growth* is not statistically significant at the 10% level, meaning that a change in GDP growth cannot explain the change in the probability of default. In regards to this finding, one can argue that the GDP of the U.S. economy at the time of issue may not be an important factor in determining default but rather a factor of interest at the time of default. However, testing this theory would not improve an investor's investment decisions as they cannot perfectly predict the future values of GDP growth. Another aspect is the difficulty of finding good proxy variables to model the macroeconomic condition of the economy. From elementary macroeconomic theory, one can understand how macroeconomic variables correlate with each other. Thus, if the economy is in a downward period, it is associated with poor performance across indicators. In respect to our model, this means that GDP growth may in theory not be insignificant, but the unemployment coefficient may already capture the effect.

	Loan Status				
Predictors	*Estimates*	*df/dx*	*Std.Err*	*p*	
gdp_growth	-0.02	-0.00	(0.00)	0.206	
unemployment_growth	0.77	0.19	(0.03)	**<0.001**	***

Table 8: Extraction of Regression Output Model 2

Unemployment growth, on the other hand, is a highly significant variable. The positive sign of *unemployment growth* shows that when unemployment is increasing, so is the probability of default. This finding follows economic intuition, as a higher unemployment rate means that jobs and incomes are lost and thereby reduce the borrower's ability to repay debt. Figure 12 shows that the unemployment growth rate is among the 15 most important variables predicting loan default in Model 2. Previous studies found that during a recession the economy is plagued by a higher risk associated with loans (Bikker & Haixia, 2002) and that the probability of default across the economy increases (Gambera, 2000). Our findings prove that these theories apply to P2P-lending market as well. Furthermore, Figure 9 in section 5.5, shows that the correlation between *unemployment* and *interest rate* is positive. This suggests that during a recession, the interest rates on new P2P-loans are higher. Hence, investors generally act rationally and demand higher interest rates to compensate for the higher risk of default in the economy.

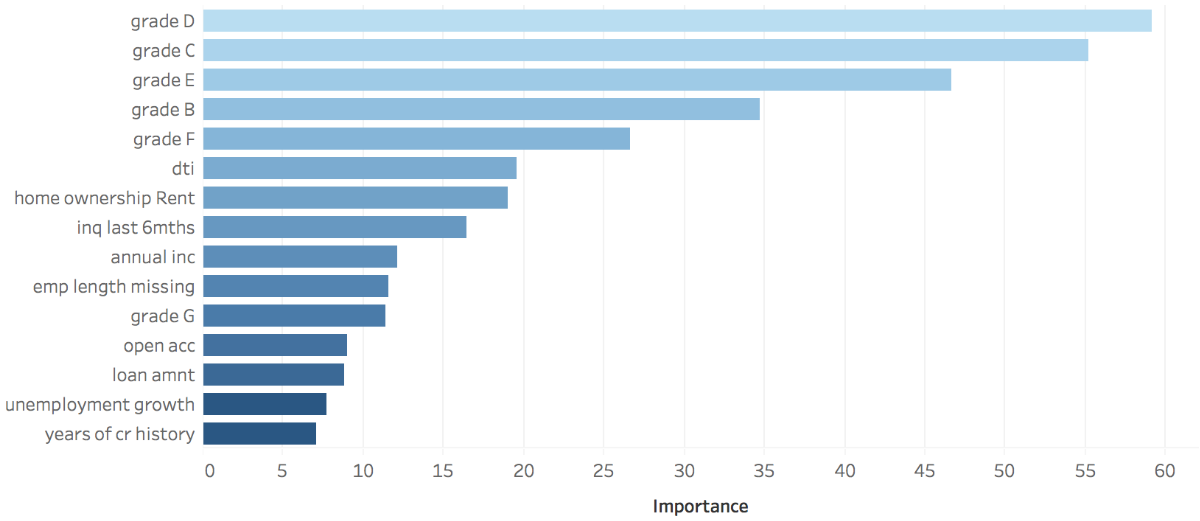

Figure 12: Variable Importance From Model 2

Figure 4 in the Data section (4.2.1) shows the evolution of the U.S. economy in the period 2008-2015. This depiction makes it clear that LendingClub was exposed to a relatively stable unemployment rate without major fluctuations. Our findings are in line with studies on other credit markets, where a negative relationship between the unemployment rate and credit market performance is found (Kaminsky & Reinhart, 1999; Sinkey & Greenawalt, 1991). Hence, our findings show that there is no reason to believe that P2P-loans are exempt from the normal business cycle.

However, LendingClub has only excised for a decade and has limited exposure to large business cycle fluctuations. This shortcoming makes it hard to model the economies effect on loan performances. Although LendingClub were around during the 2008 "Great-recession", they were getting out of their start-up stage. In particular, there is no way to deduce that the default in this period was due to the recessionary economic condition or simply the result of the lack of competence regarding P2P-lending. However, there is no direct data to model the impact of a negative turn in the economy and the period is not long enough to conclude that our findings are consistent over time. Furthermore, one can only speculate how P2P-lending will perform in comparison to the market during a recession.

Robustness Check

From Figure 11 and Figure 12 *grades* are clearly the most influential variables in both Model 1 and Model 2. Triggered by this result we decide to run a model using just *grades* as an independent variable predicting default. Nonetheless, we find that the prediction abilities of this model is below Model 1 and Model 2. The same is confirmed in the models Pseudo-R^2, which is slightly worse then both the other models (Appendix A3.3). To ensure that this parsimonious model is not a better model than Model 2, we compute an LR test. The LR test has a χ^2 of 2,398.2 and 38 degrees of freedom. Thus, we reject the null hypothesis and conclude that Model 2 is the best-fitted model for predicting loan default on LendingClub's platform.

This result shows that potential LendingClub investors can better predict the probability of a borrower defaulting by looking at the borrowers loan characteristics as well as the macroeconomic condition, than by just looking at the borrowers grades. However, as found by looking at the variable importance of Model 1 and Model 2, grades are still the most informative characteristic in determining default. This finding is not surprising as LendingClub themselves have used the loan and borrower characteristics to assign grades based on the borrower's credit risk.

Further, this robustness check brings light to some of the findings from other work on P2P-lending. Although, grades have historically proved to be the most influential variable in determining whether a loan will default or not, investors on LendingClub and other P2P-lending platforms can mitigate their information disadvantage by using the information provided to them.

As presented in the literature review, there are mixed theories on whether P2P-lending platforms are more or less exposed to asymmetric information. Those who argue that P2P-lending has less asymmetric information demonstrated how borrowers could provide additional soft information to give investors a more transparent view of their qualifications. Thus, mitigating some of the information asymmetries normally found in credit markets (Chen & Han, 2012; Iyer et al., 2009). Others also associate the decrease in asymmetric information to the fact that investors have access to each borrower's characteristics before deciding whether to invest in a particular loan (Bachmann et al., 2011).

Our results support the first view. We find that adding more variables to our model provides better predictions and gives the investor more information than just including credit grades.

8.3 Part III - Expected Return and Sharpe Ratio

8.3.1 LendingClub

Part III moves into the performance of LendingClub and other credit market operators during and following the 2008 recession. The expected returns are calculated as outlined in the methodology. To ensure that this method is robust, we cross-validate our values using an alternative calculation (Appendix A3.4).

Table 10 displays the calculated return measures for each grade in LendingClub. μ_r shows the mean interest rate for each grade, $E[r_p]$ shows the expected return for an investment in a portfolio of each grade and σ_p is the standard deviation of the return in that portfolio. Lastly, the Sharpe ratio shows the risk-adjusted return for each portfolio.

	$\boldsymbol{\mu_r}$	$\boldsymbol{E[r_p]}$	$\boldsymbol{\sigma_p}$	**Sharpe**
A	7.21%	6.96%	0.13	0.53
B	10.27%	8.79%	0.19	0.46
C	13.92%	8.48%	0.24	0.33
D	17.20%	8.51%	0.30	0.27
E	19.80%	7.51%	0.34	0.21
F	23.39%	7.82%	0.39	0.19
G	23.98%	2.78%	0.42	0.06

Table 9: Expected Return for LendingClub Grades

To complement our expected return measure, we quantify the expected loss for each grade. Table 10 shows our findings where $P(D = 1)$ is the probability of default and LGD shows the average percentage of the funded amount an investor loses if the borrower defaults.

	P(D=1)	LGD	Credit Loss Rate
A	5.47%	36.5%	1.99%
B	11.20%	35.6%	3.99%
C	17.94%	36.4%	6.53%
D	23.34%	37.3%	8.71%
E	28.30%	38.3%	10.83%
F	32.84%	38.4%	12.6%
G	38.25%	41.5%	15.9%

Table 10: LendingClub's Default Rates and Loss Given Default

Overall, the results show that there are positive expected returns for investors on LendingClub's platform. As previously outlined in our exploratory data, the probability of default and the mean interest rate increases with each grade (see Table 2 and Figure 7). A natural consequence of this is that the LGD is also larger for worse credit grades. Our findings support this to an extent as LGD is slightly higher for worse credit grades. The exception is grade B. To gain a deeper understanding of the underlying behavior of our LGD's we calculate the expected time of default for each loan grade, shown in Table 11.

Grade	Default Month
A	19
B	18
C	17
D	16
E	15
F	15
G	13

Table 11: Expected Month of Default

Interestingly, we find that there is a smaller range in the expected time to default than anticipated. Grade A loans are expected to default 19 months after issue which is later than the subsequent worse credit grades. For each incremental less creditworthy grade the expected time to default is one month before the previous grade. This relation holds for all loans except for grade E and F, which both are expected to default after 15 months. Grade G loans are expected to default already after 13 months.

Table 9 shows that the expected return for all grades is significantly lower than the corresponding mean interest rate. The expected return for all grades is 7.26%. Compared to the other variables from Table 9, our expected return measures do not follow a linear relationship. In fact, our results show that an investor can expect to receive the highest return from investing in grade B loans. Further, grades C, D, E, and F are suggested to give better returns than grade A loans. In other words, only the least creditworthy grade G loans are expected to give worse returns than the safest grade A loans. These results are in line with other studies on P2P-lending and their investment returns (Golubnicijs, 2012; Möllenkamp, 2017). However, our expected positive returns contradict with the earliest studies which concluded that P2P-lending gave negative returns for investors (Freedman & Jin, 2008; Klafft, 2008). The last column of Table 9 shows the Sharpe ratio for each portfolio in the period 2008-2015. Again there is a linear relationship between the Sharpe ratio and creditworthiness, where grade A loans have the highest Sharpe ratio and grade G loans have the lowest.

8.3.2 Other Credit Markets

Corporate Bonds

Table 12 shows the past performance of Corporate bonds in the United States. For consistency, each bond grade represents an investment portfolio. The data from the Bank of America Merill Lynch shows the total return of each grade's bond index. The total return already accounts for the LGD and expected loss. From financial theories we know that investors require higher returns during weak economic conditions than in stronger economic conditions (Fama & French, 1989). Thus, to capture the effect of the recession, we have measured the average return, the standard deviation of returns and the Sharpe ratio both including and excluding the years 2008-2009.

Interestingly, grade AAA to A bonds did not have a higher return over the seven years including the recession than the five years following the recession. However, the grade BBB to CCC indexes had a higher average return in 08-15 than in 10-15. The standard deviations follow the same trend, showing that the volatility of the returns is much greater when we include the recession than in the subsequent years. The same effect is captured in the calculation of the Sharpe ratio.

	$E[r_p]$		σ_p		**Sharpe**	
	08-15	*10-15*	*08-15*	*10-15*	*08-15*	*10-15*
AAA	3.90%	4.31%	0.04	0.05	0.85	0.81
AA	4.43%	4.56%	0.04	0.04	1.02	1.17
A	5.00%	5.41%	0.07	0.04	0.66	1.18
BBB	6.9%	5.92%	0.12	0.05	0.56	1.03
BB	8.86%	7.48%	0.17	0.06	0.51	1.3
B	7.13%	6.24%	0.19	0.07	0.35	0.86
CCC	11.41%	5.44%	0.37	0.13	0.30	0.41

Table 12: Corporate Bond Performance by Grade

As expected, the mean return increases when the bonds decreases in creditworthiness and the Sharpe ratio moves in the opposite direction. For the full 08-15 time period AA bonds had the highest Sharpe ratio, with a ratio of 1.02. Subsequently, all others are significantly lower with AAA being the second highest at 0.85. The expected return for an investment in a bond portfolio was higher for BBB-CCC bonds during the time period, 08-15, than AAA-A rated bonds. These findings suggest that during a recession the investors of low-quality bonds, demand a higher return to hold these bonds in an unstable economy. This finding is consistent with bond theory, where investors receive higher returns to be compensated for holding extra risk. Thus, the risk of BBB-CCC bonds increases more during a recession than higher quality bonds.

Based solely on the weak Sharpe ratios, investors holding a corporate bond between 08-15 were not compensated for the risk they held. Comparing this result to the 10-15 time period all grades have a higher Sharpe ratio after the recession. These results imply that there is a negative relationship between risk and the Sharpe ratio for corporate bonds. In the 10-15 period, AA-BB bonds all have Sharpe ratio's slightly above 1, indicating that they provide a premium above their risk.

A common problem when calculating expected values is not capturing the true realized value. This problem can occur by limiting oneself to a short time period. The economy is constantly fluctuating, and the effects of a business cycle boom or bust can linger in the economy for several years (Reinhart & Rogoff, 2009). Thus, if one finds an expected value using observations from only a few years, one could make concluding arguments based on an anomaly during that time frame. This deviation is also seen in our corporate bond returns shown in Table 12. Including or excluding 2008 and 2009 from our analysis gives a different representation of the attractiveness of corporate bond investments.

As emphasized throughout this paper an investor should strongly evaluate credit risk when making investment decisions in the LendingClub loans and corporate bonds. Table 13 shows the default rate, recovery rate and credit loss rate of corporate bonds of each credit grade.

	Default Rate	**Recovery Rate**	**Credit Loss Rate**
AAA	0.00%	47.9%	0.00%
AA	0.09%	47.9%	0.05%
A	0.12%	47.9%	0.08%
BBB	0.33%	47.9%	0.20%
BB	0.67%	28.8%	0.43%
B	2.02%	28.8%	1.28%
CCC-C	9.56%	28.8%	5.73%

Table 13: Moody's Corporate Default and Recovery Rates

Consistent with LendingClub, the default rates increase as the bond grade worsens. The same trend is observed for the credit loss rate. Although they follow the same trend, LendingClub's default rates are much higher than corporate bonds. Moodys expect less than 1% of grade AAA-BB bonds to default. The only bonds with relatively high default rates are CCC-C bonds. The opposite trend is seen in the recovery rate, where the recovery rate decreases for lower quality bonds. This decrease shows that investors of lower bond qualities lose more of their investment when bonds default. Again, this is consistent with LendingClub.

Government Bonds

Besides investing in corporate bonds, U.S. consumers can invest in credit markets by purchasing government bonds or by placing their money in CDs. Table 13 shows the performance of CDs in the U.S. and the 3-Year Treasury bond. These investment opportunities are relatively risk-free, and an investor of these assets is mainly exposed to interest rate risk.

The U.S. 3-Year Treasury is a grade AA bond with a 0.186% 3-year cumulative probability of defaulting (Y. Liu et al., 2017). The standard deviation on the 3-Year Treasury bond is extremely low, at 0.006 and 0.003 for the two time periods. Further, the mean return is 0.77% and 1.03%, reflecting the safety of these investments. This shows that in comparison to the riskier corporate bond investment alternatives, an investor on average gets lower returns in the government bond market but is less exposed to risk.

	$E[r_p]$		σ_p		**Sharpe**	
	08-15	*10-15*	*08-15*	*10-15*	*08-15*	*10-15*
3-Year Treasury Bond	1.03%	0.77%	0.006	0.003	1.324	1.855
Certificate Deposit	0.61%	0.23%	0.940	0.236	0.654	0.990

Table 14: Certificate of Deposit and 3-Year U.S. Treasury Performance

Certificate Deposits

The second row of Table 14 shows that CDs have lower returns and higher volatilities than government bonds. Further, in both time periods, the 3-Year Treasury bond's Sharpe ratio outperforms the CD's. Therefore, the risk-return alignment for a 3-Year Treasury bond is more favorable than for a CD.

8.4 Part IV - Comparing LendingClub With Other Asset Classes

Part IV of our methodology compares the credit rating grades of Moody's and LendingClub. This comparison gives insight into the different risk levels in the credit markets.

Throughout the analysis, we find many similarities between LendingClub and the other credit assets. First of all, there is a consistent negative relationship between default rates and creditworthiness. Further, we find that higher volatilities in return are positively related to the mean interest rate but negatively related to the Sharpe ratio.

Regardless of the two time periods presented, the Sharpe ratio for AAA-BBB corporate bonds is higher than for any LendingClub grade portfolio. Directly interpreting this measure suggests that risk-neutral investors aiming to maximize their return, without taking on extra risk exposure, should invest in high-quality corporate bonds over any

LendingClub loan portfolio. In terms of the Sharpe ratio, however, the 3-Year Treasury bond outperformed both LendingClub and corporate bonds.

Table 13 shows the default and recovery rates for corporate bonds. For the safest investment option, the default rate and the credit loss rate is 0.0% showing that credit rating agents have strong faith that these bonds will not default. In comparison, LendingClub's least risky loan option has a 5.47% probability of default and an expected credit loss of 1.99%. These results confirm that there is a difference in risk between the two grading methods. Further, the default rate and the recovery rate suggest that LendingClub's investors are taking on excessive risk. This result is consistent with the findings suggested by our Sharpe ratio's and Emekter et al. (2015)'s results. In regards to the probability of default and the credit loss rate, LendingClub's grade A loans lie somewhere between Moodys'grade B and CCC-C bonds. The remaining LendingClub loans have higher default rates than C graded bonds, which is seen by comparing the results in Table 10 and Table 13.

The expected return is the only variable that would suggest LendingClub to be an appealing investment option. The expected return on LendingClub's grade A loans is equivalent to the expected return on BBB-BB corporate bonds. The similar expected return suggests that an investor funding a LendingClub loan and an investor holding a BBB or BB bond are exposed to the same risk. However, our results do not support this claim. Instead, LendingClub 's investors face higher probabilities of default and LGDs.

In our Theoretical Framework, we presented the certainty effect explaining that investors are risk-seeking in choices ensuring sure losses (Kahneman & Tversky, 1979). This concept is one possible explanation for why investors are investing in P2P-loans with lower expected values than other credit assets. If investors are looking for a risky gamble, P2P-lending acts as an appealing alternative to Junk bonds. In comparison, a rational risk-neutral investor would want to minimize risk and maximize their return by investing only in the most attractive loans (Möllenkamp, 2017). In light of our results, we, therefore, conclude that investors in the P2P-lending market are risk-seeking and irrational. Unlike Golubnicijs (2012), we conclude based on our empirical study that P2P-lending market is not an attractive asset class for rational investors.

9 Future Uncertainties

9.1 Regulation

Our research shows that literature discussing regulation within P2P-lending exists, but a detailed analysis of whether regulation will change the characteristics attracting investors to P2P-lending is missing. Shortly after the rise of P2P-lending, the Security Exchange Commission (SEC) recognized these platforms as selling securities. Thus, to oblige with The Securities Act of 1933 platforms must register at the SEC (CNBC, 2009). The main purpose of this act is to ensure that information is translucent and available between all market participants (Verstein, 2011). Currently, the U.S. P2P-lending regulation is separated into two. The SEC regulates the lender side, while the Federal Trade Commission and Consumer Financial Protection Bureau are responsible for the borrower side (Nemoto et al., 2019). Despite being under the SEC's regulation, investors consider the market to be relatively unregulated. This view arises because there are no specific regulations that capture P2P-lending and market participants must follow relevant regulations from other markets (Chaffee & Rapp, 2012). In particular, LendingClub must adhere to the regulatory laws of the lending market, such as the Dodd-Frank (Chaffee & Rapp, 2012). Further, the view that P2P-lending is unregulated emerges from the difference in regulatory framework between P2P-lending and traditional credit institutions (Buchak, Matvos, Piskorski, & Seru, 2018).

There are strong reasons to expect regulations to tighten in the future and that these regulations can change the attractiveness of P2P-loans as an investment option. Regulators around the world are continuously introducing new regulations on P2P-lending markets. Among these are India, the UK, Germany and China (Ramesh & Gandhi, 2019; Walker, 2016). The P2P-lending market in China faced extreme growth from early 2007 to mid-2018. The Chinese P2P-lending market was fairly unregulated until the Chinese government was forced to step in during 2018, following a large number of loan defaults. The regulators hoped to fix the hot market, but instead, the intervention caused a further investor flight and more platforms to default (Mullen & Rivers, 2018).

One reason for the need of further regulation is the threat of increased financial fraud in the Fintech world. As pointed out, the literature on P2P-lending markets mostly focuses on the credit risk part of P2P-lending. There is therefore limited academic attention to the risks of financial crimes. A part of the default wave in China was the unravelling of investment scams (S. Zhang & Glenn, 2018). The events in China have brought a heightened awareness of the presence of financial fraud on P2P-lending platforms. As a part of the SEC regulation, LendingClub must publicly publish all their loan information. This requirement provides some security against large scams occurring. However, there are still many who believe that P2P-lending platforms place investors at greater risk for crimes than other investment options. Xiao, Li, and Zhang (2018) highlights that P2P-lending platforms should eliminate the risk of three crimes: Ponzi schemes, credit fraud, and money laundering. Currently, P2P-lending platforms use scrutiny systems to decide whether borrowers obtain financing and at which interest rate. These systems do not, however, capture the potential for criminal behaviors. Thus, P2P-lending, which so far presents higher cyber-security risks, is still in need of stronger regulatory methods to limit the industries weaknesses (Ng, 2018).

Borrowers are required to provide a lot of personal and sensitive information about themselves. For a P2P-lending platform to survive, it is vital that they can ensure their customers that this information is stored safely and not misused. In 2018, the new General Data Protection Regulation (GDPR) reform came into effect in the European Union. As a result, European P2P-lending platforms have to ensure that their business operations follow these regulations. Experts expect GDPR to be a continuously updated standard and that its application will quickly spread. Thus, the current U.S. Data Protection laws are anticipated to get stricter and more aligned with the new GDPR requirements (Buttarelli, 2016). For P2P-lending platforms, this means that they may face future challenges regarding the storing and use of their borrower's information, information which is vital for their current business model (Tikkinen-Piri, Rohunen, & Markkula, 2018). For an investor this will mean lower returns, resulting from the increased platform and transaction costs.

Another concern is contingency between investors and platforms. If investors start to lose faith in the attractiveness of P2P-lending and investors stop investing in P2P-loans, a domino effect can take place. The quick loss of investors can destroy the platforms ability to survive. This domino effect was partly the cause of the market collapse in China.

Before the 08-09 crisis, the financial market saw an increase in the origination and use of new financial instruments (Rajan, 2005; Taylor, 2009). Their market value continued to grow, and risk exposures were hard to estimate. When the economy turned, the financial institutions risk exposures were revealed to be largely underestimated, and the market crashed (Jorion, 2009). Post-crisis, the market saw an intensive implementation of regulations and organized exchanges were implemented to regulate and control risks (Eichengreen, 2010). There are two main takeaways from this episode that can be applied to the P2P-lending market. Firstly, it is hard to assert how new trends in financial markets will perform during economic downturns. Secondly, necessary regulation comes in too late. Often because the true risks are not known until exposed.

The problem of asymmetric information between the platform and its participants is often emphasized as a reason for the need of more regulation (Käfer, 2018). In their current business model, LendingClub determines the loan grade and interest rate on their loans. Asymmetric information between the investor and the platform arises as the investors hold the risk of the platform's decisions. New regulations may alleviate this unfavourable incentive by requiring P2P-lending platforms to hold parts of the loan risk.

Before ending this section, it is important to stress that finding the right regulation is not an easy task. That is why experienced committees and markets are continuously updating their regulatory framework. The term "learn from the past" seems to apply to the financial market. This is where LendingClub's and the other P2P-lending platforms brief existence comes in short.

9.2 Competitive Environment

Another limitation of the presented literature is the lack of analysis on the future competitive environment of P2P-lending. Impending changes in the credit market is a considerable risk for P2P-lending platforms as they can lose their competitive advantage. In particular, worries regarding the Federal Reserve rates, the banks market position and technology, create uncertainties concerning the attractiveness of P2P-lending.

The low returns on CDs and Treasury bills during the finical crises forced investors to look for investment returns elsewhere. Since the end of 2015 to the end of 2018, the Federal

Reserve has increased the benchmark interest rate nine times. At the end of 2018, they changed the interest rate by 25 basis points from 2.25% to 2.5% (Reserve, 2018). The increase in the interest rate signals that the Federal Reserve is confident in the economy (Rushe, 2018). This confidence is a result of several years of reduction in the national unemployment rate. The higher interest rate can change investors views on P2P-lending. Specifically, investors may not view P2P-lending as a promising investment in a time of higher interest rates because they can earn a higher rate through traditional banks. The rising yields on CD's and Treasury bills could narrow the gap between the "risk-free" rate and P2P-lending returns, making P2P-lending less attractive. In practise this means that the return on saving money in a CD will be close to the return received by investing in a grade A loan, but with less risk. If people still want to invest in P2P-lending, one can assume that they will be more interested in grades B-D loans, with higher expected returns (Guillot, 2016).

Further, bank institutions have the advantage of economies of scale, stronger brand recognition and established trust. Despite their stronger positions, banks are aware of the demand for alternative online lending and want to take part in it. However, legacy systems and the complex structures hold them back and make it harder for them to innovate. Fintech companies, on the other hand, have the advantage of an innovative mindset, agility, consumer centring perspective and digital infrastructure. Thus, in order to remain competitive, banks have to decide whether to collaborate with Fintech companies or innovate themselves (EY, 2017)

J.P Morgan Chase is among the top three Small Business lenders in the U.S. In 2006, they partnered with the online lending startup OnDeck and are utilizing their technology to issue loans to small business quickly (Macheel, 2017). By using OnDeck's technology they can: pre-score their customers based on the data from their existing relationships, reduce the application process, reduce the decision time from one month down to seconds and deliver the funds the following day. This example shows that banks are willing to engage with P2P-lending companies and that there is room for future collaboration.

At the same time, the threat of market disruption has pressured incumbents to innovate more rapidly. Major banks have launched new online or mobile initiatives aiming at reclaiming their market shares at a lower cost than previously. In 2016, Goldman Sachs launched its new digital initiative called Marcus. Marcus is an online lending platform offering unsecured consumer loans and expects to generate $1 billion in revenue by 2020 (Renton, 2018). Being direct lenders and due to the size and strength of Goldman Sachs' business, one can suspect that Marcus will be able to handle a recession better than other P2P-lending platforms. Although it is not the same system as P2P-lending, there are reasons to believe that Marcus can become a leader in the online lending space and a threat to P2P-lending platforms.

A recent study showed that 71% of banks were interested in partnering with a third-party digital platform for consumer loans and nearly 80% of banks were interested in using technology to support their small business lending (American Bankers Association, 2018). In other words, there is no doubt that banks are going to take part in the future of the online lending market. However, it is difficult to predict what role banks will have. There are several benefits for P2P-lending platforms to collaborate with banks, including access to large customer databases. Banks also act as a fund supplier for P2P-lending platforms and can help them improve risk management. Considering the high risk associated with P2P-lending found in our analysis, this is an important benefit (Asian Banker Research, 2017).

10 Discussion

Thus far, we outlined several sources of risk in P2P-lending. We stress that credit risk is the largest concern but also give light to the nature of liquidity risk, regulatory risk, fraud risk and market risk. In other words, P2P-lending is far from a risk-less asset class.

10.1 A Junk Bond Investment

The findings from the empirical analysis conducted in this paper confirm that P2P-lending is a relevant asset class, but only for risk-loving investors. The mean interest rates for each grade looks promising and gives the illusion of being a high return investment. However, due to high default rates and high volatilities in the realized returns, the expected returns from P2P-lending are less inviting. In fact, we find that investing in P2P-loans is closest comparable to investing in Junk bonds.

Junk bonds are also known as speculative bonds. The alternative name depicts the speculative nature many investors of Junk bonds have. Although some investors are attracted to Junk bonds because of their high yields, others take these positions with the belief that the bond price will rise. If an investor believes that the firm's value or financial position will improve in the future, they can get great returns by selling at a higher price. Using this line of thought, one can see that investors who have done their research can justify these high-risk investments. However, this strategy does not apply to P2P-loans. In corporate bonds, one can use a value-investing strategy, perform analysis and form opinions on the corporations future. Applying these tools is not possible in P2P-lending as the borrower's information is anonymous. Therefore, all research and analysis are limited to the information provided by the platform.

10.2 Investor Behaviors in P2P-Lending

Following the above discussion, it is natural to discuss why investors choose to engage in the P2P-lending market. The empirical findings suggest that P2P-lending is not a profitable investment compared to other credit assets when considering its risk. In other words, a rational investor according to Sharpe (1966), should not choose LendingClub as their investment option, but rather invest in government bonds or investment grade corporate bonds. A second argument is that investors in P2P-lending are not directly irrational but lack the financial knowledge needed to make rational decisions. Klafft (2008) found that P2P-lending platforms rely on rational, risk-neutral and profit-oriented investors in order to remain operating. Our findings and analysis do not suggest that P2P-lenders act rationally. Combining Klafft (2008)'s and our findings suggests that the future of P2P-lending platforms is uncertain.

The literature presented papers that found evidence of herding behavior in P2P-lending markets (Herzenstein et al., 2010; E. Lee & Lee, 2012). When investors herd, economists recall that their behaviors can be either rational or irrational (Bikhchandani & Sharma, 2000). The expected returns from Part III suggest that P2P-lending markets are currently characterized by herding behavior. Herding behavior stems from investors engaging in P2P-lending markets solely because other investors do and not because of the fundamental attractiveness of the investment opportunity. When P2P-lending platforms emerged, investors faced a lack of investment opportunities due to low interest rates and unstable markets. However, despite the stabilization of competing markets, P2P-lending has continued to grow (see Figure 1 section 3). The performance measures presented in Table 9 (section 8.3.1), shows that P2P-lending is not an attractive market for rational investors. Thus, herding behavior is a highly possible explanation for the continued market growth.

In addition to the above results, we found evidence that P2P-lending markets are overvalued. First of all, a major motivation to study the P2P-lending market is the lack of literature and financial theories covering this market. It is thus reasonable to suggest that the general knowledge regarding P2P-lending is below the knowledge of other asset classes. Thus, as reasoned by the detected herding behavior, investors may think P2P-lending is more appealing than it really is. Second, the Chinese P2P-lending market proved to be a hot market. The worry regarding hot markets arise when the investors view of the asset market change. In the event of an increase in default rates, investors will become aware of their true risk exposure. Consequently, investors may start leaving the P2P-lending market causing the herding investors to follow their exit strategy. The investor flight generates an operating problem for P2P-lending platforms as they no longer receive the funding they need to survive. This reasoning is in line with the events in China and one fears that a similar situation will occur in the U.S. P2P-lending market.

In addition to recognizing herding behavior as a part of P2P-lending's rapid growth, herding behavior is detected during loan decisions. Herzenstein et al. (2010) found that P2P-lending investors would choose a loan solely on the fact that others have chosen to invest in that loan. In our empirical analysis, we have outlined variables that are significant in determining default. If investors are herding when choosing which loan to fund, they ignore essential characteristics and can select loans that according to our results are riskier.

10.3 Asymmetric Information in P2P-Lending

In our findings, we briefly mentioned that we find evidence of increased information sharing between the LendingClub investors and the platform. In particular, we prove that investors can gain additional information about the borrowers creditworthiness by employing the results from our logistic regression models. This finding is consistent with Iyer et al. (2009) and Chen and Han (2012). However, we argue that based on our findings in Part IV, P2P-lending investors are still disadvantaged by information asymmetries. We found that investors of P2P-lending are either risk-seeking, irrational or lack financial expertise. The two later are consistent with the literature (Freedman & Jin, 2008; Klafft, 2008). Further, LendingClub uses a letter grading system to express the riskiness of their loans. In comparison, to more recognized grading systems provided by known credit rating agencies such as Moodys, the LendingClub's assigned grades are far riskier. Thus, the true risks of P2P-lending are not obvious. This finding shows that although grades are the most important variables in predicting default, their opaque nature create increased information asymmetries between the platform and investors.

Further, to comply with data protection regulations, P2P-lending platforms are obligated to make the borrower anonymous by removing all identifiable information. The removal of information restricts the investors from performing further research before making a loan decision. Determining whether there is more or less asymmetric information present in P2P-lending markets compared to other credit markets is outside the scope of our paper. However, we have provided evidence that this market inefficiency also affects P2P-lending markets. In addition, we suggest that eliminating the presence of asymmetric information is not as simple as previous literature indicates.

10.4 The Risks of P2P-Lending

A part of answering our research question is to determine how P2P-lending platforms will perform in the future. The paper addresses the macroeconomic condition, future regulation and the competitive environment as three factors likely to impact the future of P2P-lending platforms. As outlined in our results, we find a significant positive relationship between the unemployment growth rate and default rate, indicating that when the economy is weak P2P-loans perform worse. We also found a positive relationship between interest rates and unemployment growth rates. In short, P2P-loans are riskier during weak economic conditions.

Bond risk premiums tend to have higher risk premiums during weak economies and lower risk premiums in strong economies (Cochrane & Piazzesi, 2005). Further, evidence on the U.S. market found that corporate bonds tend to pay higher returns during economic downturns, while government bonds and CDs tend to have poor returns (Ielpo, 2012). Moreover, low-quality bonds are more exposed to systematic risks, such as the market condition, than high-quality bonds (Cornell & Green, 1991). The reason for a higher corporate bond return is because investors fear defaults and sell their bonds. Thus, the bond price decreases and the yield increases. Additionally, evidence shows that corporate bonds default more during economic contractions (Athanassakos & Carayannopoulos, 2001). Our results show that investment grade bonds pay lower returns in a recession while Junk bonds pay higher returns. Thus, in economic downturns, investors are risk-averse and prefer to hold safer assets. This preference is confirmed by observing the government bond market during the recession. Due to their risk-free nature, the demand for government bonds increases during a recession. The increase in demand drives the prices up and thus, the yield decreases.

In line with other credit markets, CDs also tend to give poorer rates during economic downturns. Again, this finding is consistent with our results. Unfortunately, the timing of the last financial crisis makes it hard to give a confident indication as to which asset class P2P-lending resembles the most. On the one hand, interest rates for new loans rise during economic downturns giving investors higher returns. On the other hand, the overall default rates increase. The final effect is therefore ambiguous. One may question whether the higher interest rates compromise for the increase in credit risk. Another economic downturn is needed before this question can be further answered.

The uncertainty regarding future regulations is also a vital part of determining the future appeal of P2P-lending markets. As previously outlined there is a general agreement that new regulations will emerge in the future. These new regulations will likely try to protect investors from large credit losses, either by reducing fraudulent activities, spreading the risk between platform participants or other methods. A brief interpretation might suggest that investors are better off with more protection. However, as we have repetitively emphasised in this paper, risk equals returns. If regulations decrease the risk associated with investing in P2P-lending, then investors interest rates will likely decrease as well. Stricter regulations of the P2P-lending market may require platforms to take an active role in the risk allocation of their loans. A more active position will force platforms to change their current business model and increase their operating costs. Increased operating costs will spill over on borrowers and investors through higher fees and thus, lower the total return for investors. Therefore, there is full reason to suggest that future regulations can change the current competitive advantage of P2P-lending platforms.

Besides increased operating costs, there are other threats to the competitive advantage of P2P-lending markets. Currently, P2P-lending's competitive environment consists of all credit lending corporations, whether they are Fintech or traditional institutions. The rise of interest rates and the decrease in credit requirements are a direct threat to P2P-lending. The rising interest rates offered by banks and other credit institutions introduce interest rate risk for P2P-lending investors. Hence, an investor must consider the opportunity cost of having their money locked in P2P-loans with fixed rates. Although several P2P-lending platforms operate with secondary markets, it is not easy for an investor to liquidate without losses. This liquidity risk can scare off potential lenders who prefer asset classes with greater liquidity and less risk. This reasoning supports the argument that future P2P-investors are risk-loving.

Another meaningful change is that banks are beginning to develop competing technologies. Technology and data processing have been dominant features of the P2P-lending markets competitive advantage. As outlined in section 3.2.1, their technological advances allowed them to keep their processing times and costs down. However, banks have the opportunity to outperform P2P-lending with their own technologies, due to their customer base, trust, brand recognition and financial resources. Banks also have the advantage of accessing behavioral and historical data which can eliminate the advantage P2P-lending markets have today. If banks outperform P2P-lending and borrowers no longer turn to P2P-lending platforms, then P2P-lending will not be a relevant asset class for investors, nor an asset class at all.

10.5 Forward-Looking Benefits

The discussion so far has presented a relatively negative view of P2P-lending as a relevant asset class for investors. The following discussion will highlight some of the positives views we have uncovered during our analysis.

In 2017, LendingClub decided to remove grade F and G loans (LendingClub, 2019). Our results show that the volatilities of grade F and G loans were high with corresponding low Sharpe ratios. Grade G loans in particularly performed terribly with a Sharpe ratio of 0.06 and an expected return of 2.78%. Additionally, the LGD's were around 40%. In other words, our results provide no evidence of rational investment in these grades. In fact, one can question why loans in these grades were even funded in the first place. The decision to remove grade F and G loans reflects that LendingClub is critically evaluating their products and shows they are devoted to offer the best experience for their investors. As discussed, P2P-lending platforms have investors without financial expertise and who are unaware of their risk exposure. By removing these grades, LendingClub eliminates the chance of these investors suffering from big losses.

There is still a way to go before P2P-lending platforms lose their competitive advantage. The technologies underlying P2P-lending platforms have revolutionized the credit market, and banks are recognizing the benefits of these technologies. In other words, it is safe to say that P2P-lending technology has come to stay. However, P2P-lending markets are forced, like any other institution, to keep innovating and exploring new business opportunities to remain competitive in a continuously innovating financial market. To avoid direct competition with banks, it can be beneficial for P2P-lending platforms to partner with banks in the future. From an investors perspective, a bank partnership will give them a bigger safety net on their investments, especially in the case of an economic downturn.

Investment theories highlight the importance of diversifying investments. In our study, we have aggregated each loan grade into a portfolio and studied these seven portfolios independently. Thus, there is room to argue that sophisticated portfolio management can improve the returns on investments in P2P-lending. The main goal of diversification is to reduce the volatility of the investment return. By diversifying investments across loans, the loss exposures are limited, if certain loans default. On P2P-lending platforms, investors themselves decide how much of each loan they want to fund. The only restriction is the minimum investment of $25 for each loan. Hence, an investor can diversify a $1,000 investment through 40 loans if they wish. Along the lines with Emekter et al. (2015) and Serrano-Cinca et al. (2015), we determined loan and borrower characteristics that can guide an investor to choose loans less likely to default. An investor creating investment strategies using these findings to diversify their investments are likely to get results that place LendingClub in a better light than ours.

Although the negatives may outweigh the positives, it is still important to present both sides before drawing a conclusion.

11 Conclusion and Future Work

The objective of this thesis has been to analyze the future of P2P-lending as a relevant asset class for investors. For this purpose, a four-part methodology, an analysis and a discussion are conducted.

The empirical study uses data from LendingClub, the biggest U.S. P2P-lending platform and compares it with CDs, corporate bonds and government bonds. The first two parts of our methodology use econometric methods and logistic regression to find determinants of default. From our results, we find 22 variables, and the macroeconomic condition to be significant predictors of default. The latter two parts compare the risk and returns of LendingClub with the other credit assets. Specifically, we look at the expected return, probability, LGD and Sharpe ratio.

Our main finding is that P2P-lending is a relevant asset class for risk-seeking investors. Even though high interest rates are an appealing characteristic for investing in P2P-lending, we find that the expected return on LendingClub's loans do not compensate investors for the risk they take. Further, we find that losses are higher and more probable than in the other asset classes. In comparison to corporate bonds, we find that LendingClub's grade A loans default rate is comparable to B-CCC bonds, and the subsequent grades have higher default rates than grade C bonds. Based on these comparative analysis', we conclude that a grade A P2P-loan is an investment alternative equivalent to Junk bonds. Hence, a rational investor should in theory not be choosing P2P-loans over government and investment grade corporate bonds.

Thus, our results show that the risks are far greater than the returns. In addition to credit risk, we find P2P-investors to be exposed to regulatory, market and fraud risk. These findings support previous studies (Guillot, 2016; Moenninghoff & Wieandt, 2013; Tao et al., 2017). To our knowledge, we are the first to empirically find a negative relationship between the economies macroeconomic condition and the default rate on P2P-loans. These findings show that P2P-lending does not appear to be less risky in the future and further supports our main finding.

The last contribution of this thesis regards the significant borrowers characteristics we find using logistic regression. In particular we find grades, debt to income, employment, small business, and annual income to be significant and important variables in predicting default. Further, we find by using unemployment growth as a proxy for the macroeconomic condition, that the state of the economy is a significant determinant of default. This last findings proves that P2P-lending market are like other asset classes sensitive to business cycle fluctuations and investors must account for this risk. This further stresses that P2P-lending is a highly risky asset class.

Based on our results, one can question why the P2P-lending market is growing and continuously attracting new investors. In the third part of our empirical study, we find that when investing in P2P-loans, investors act irrationally. Further, our findings supports the previous literature that irrationality and lack of financial expertise are characteristics of P2P-lending investors (Herzenstein et al., 2010; Klafft, 2008). Alike, Krumme and Herrero (2009) and E. Lee and Lee (2012), we also find evidence of the presence of herding behavior in P2P-lending markets.

To sum up, under the assumption, that investors maximize returns while minimizing risk, investors should stay away from investing in P2P-loans. If, despite these low risk-adjusted returns, investors still insist on investing in P2P-loans, the first two parts of our analysis yields valuable insight to reduce the default risk in their investments.

11.1 Future Work

Last, there is still room for a lot of work around Peer-to-Peer lending. As the P2P-lending market is a considerably new market and still in the development stage, further analysis with a longer time-frame and more diverse macroeconomic conditions will check the robustness of our results. Our dataset had some limitations and the short time frame was a particular strong weakness.

Broadness

In our paper, we seek to answer whether P2P-lending is a relevant asset class. Although we are analyzing the market as a whole, our empirical study used LendingClub as a single platform to represent the market. Performing the same analysis on LendingClub's main competitor Prosper would cross-validate our results. This validation would ensure that our results can be aggregated across the U.S. market. Further work could also include international markets to see whether P2P-loans around the world have the same risk levels as this paper finds in the U.S. market.

Methodology

We applied logistic regressions to establish delinquency rates and the determinants of default. Future work may include alternative statistical methods to assert that the optimal results are obtained. K-Nearest Neighbors, Support-Vector machine and Bayesian probabilities are appropriate methods that could be tested.

Further Areas

Briefly discussed in this paper are the opportunities to diversify P2P-lending investments. As diversification strategies are outside the scope of this paper, we do not consider the performance of diversified P2P-loan portfolios. To further analyze the risk-return relationship of P2P-lending, and to see whether a P2P-loan investment could be appealing to investors, further research could perform strategies from portfolio theory on our dataset. Another interesting aspect to investigate is whether our results in Part I can be used to increase the expected return on LendingClub's loans.

Another area for further research is to calculate how risk-seeking P2P-lenders are. Building on expected utility theories the risk parameter of a P2P-lending investor could be calculated. Lastly, our methodology can be used to compare P2P-lending to riskier asset classes such as the equity market. Our paper studied the relevance of investing in P2P-loans compared to other credit investments because of the structure of P2P-loans. However, this paper finds P2P-loans to be far riskier than alternative credit investments, and thus a comparison to equity markets may be more appropriate.

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Appendix

A1 Data

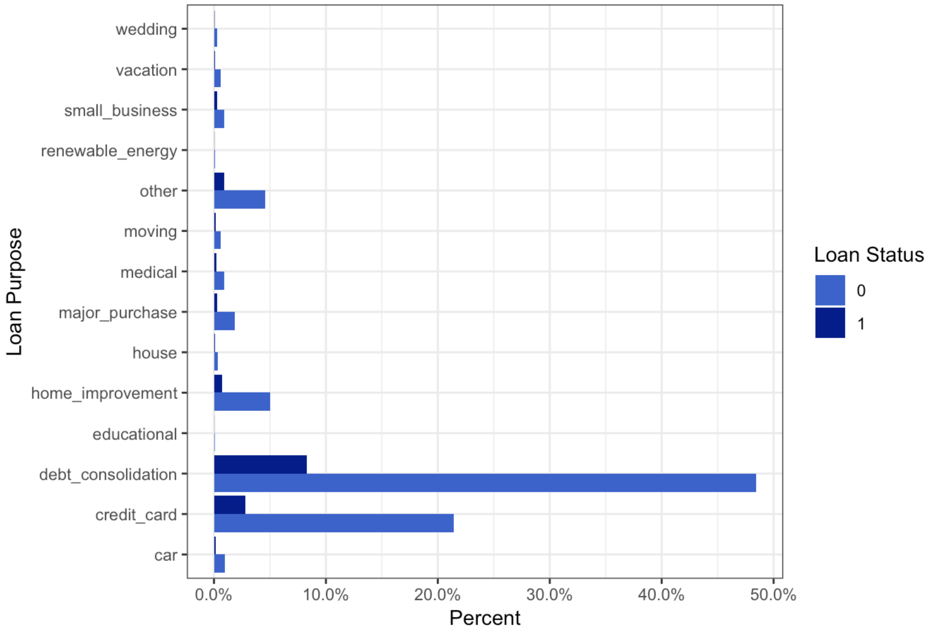
A1.1 Summary Table of The Data

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
loan_amnt	615,826	12,484.920	7,781.481	500	6,625	16,000	35,000
int_rate	615,826	0.120	0.039	0.053	0.089	0.145	0.290
installment	615,826	413.638	259.301	14.010	220.110	543.940	1,445.460
annual_inc	615,826	72,573.570	66,408.430	3,000	43,000	87,000	9,000,000
dti	615,826	17.565	8.242	0.000	11.350	23.330	39.990
delinq_2yrs	615,826	0.315	0.869	0	0	0	30
years_of_cr_history	615,826	15.538	7.601	0	10	19	70
inq_last_6mths	615,826	0.695	0.994	0	0	1	33
open_acc	615,826	11.260	5.231	1	8	14	84
pub_rec	615,826	0.206	0.608	0	0	0	86
revol_bal	615,826	15,590.400	22,106.990	0	5,808	18,765	2,904,836
total_acc	615,826	24.494	11.764	1	16	31	169
total_pymnt	615,826	13,505.990	9,030.470	0.000	6,777.978	17,934.140	51,912.520
acc_now_delinq	615,826	0.005	0.077	0	0	0	14
chargeoff_within_12_mths	615,826	0.009	0.108	0	0	0	10
delinq_amnt	615,826	11.346	671.606	0	0	0	94,521
tax_liens	615,826	0.051	0.413	0	0	0	85
unemployment	615,826	6.170	1.153	5.000	5.100	6.933	9.933
inflation_cpi	615,826	0.966	0.875	−1.623	0.110	1.682	5.303
gdp_growth	615,826	0.530	0.444	−2.164	0.123	0.825	1.254

Summary Table of The Data

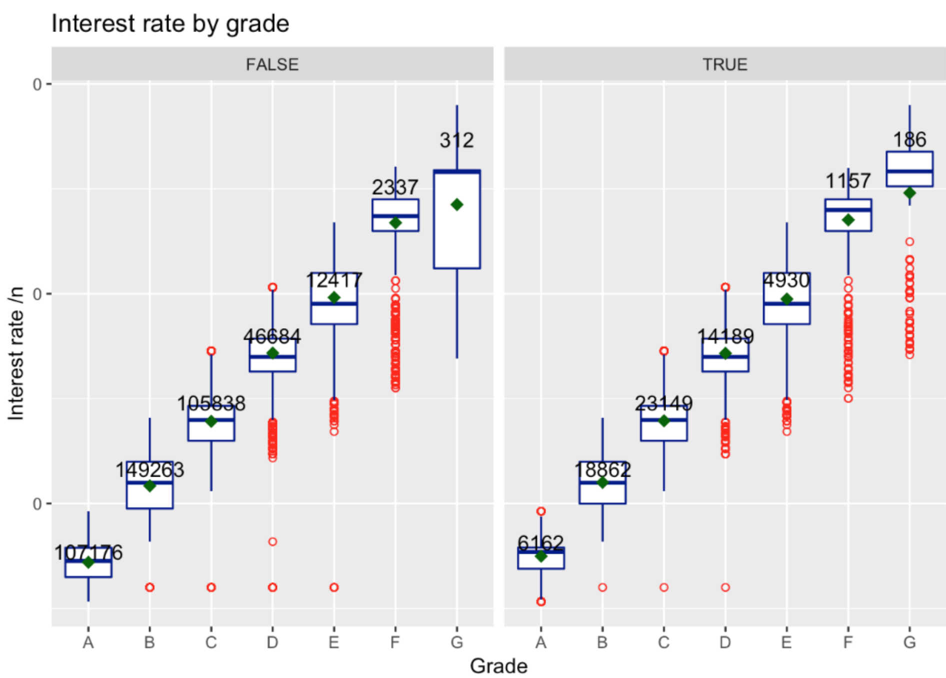
A2 Exploratory Data

A2.1 Default Rate by Purpose

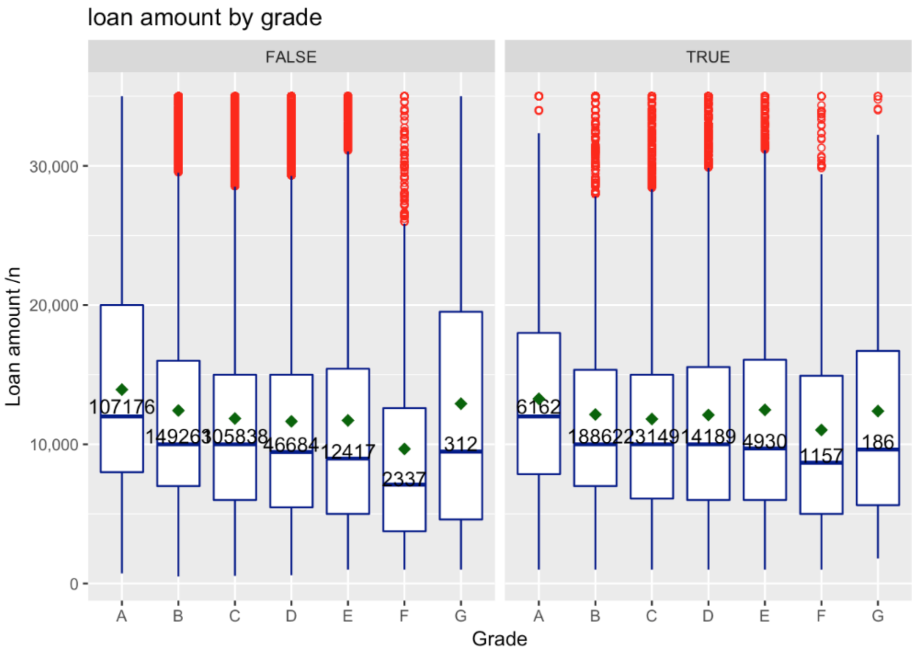


Default Rate by Puropse

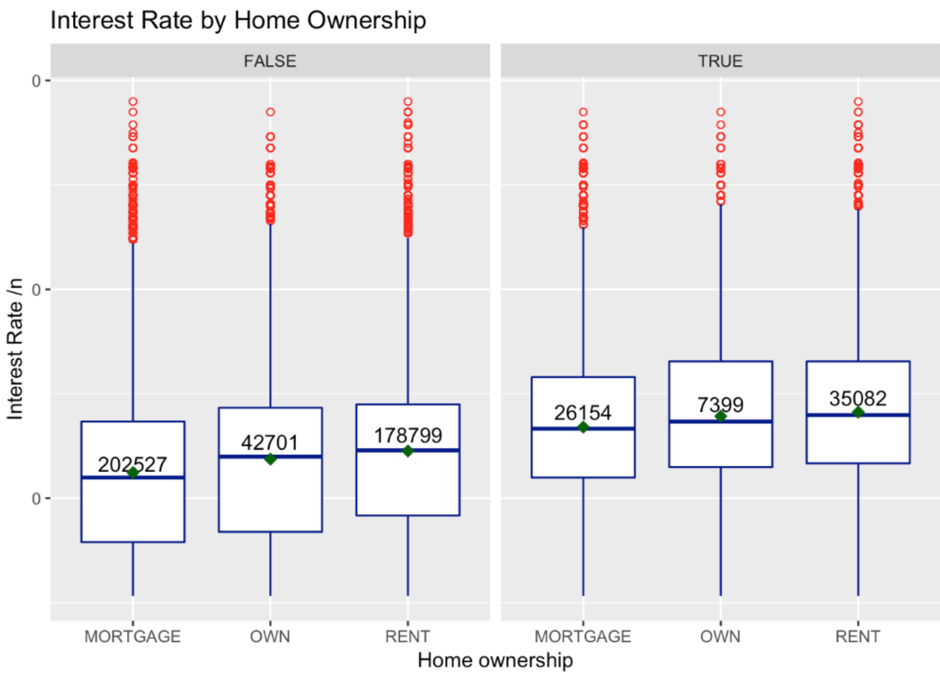
A2.2 Outlier Detection



Boxplot: Interest Rate by Grades

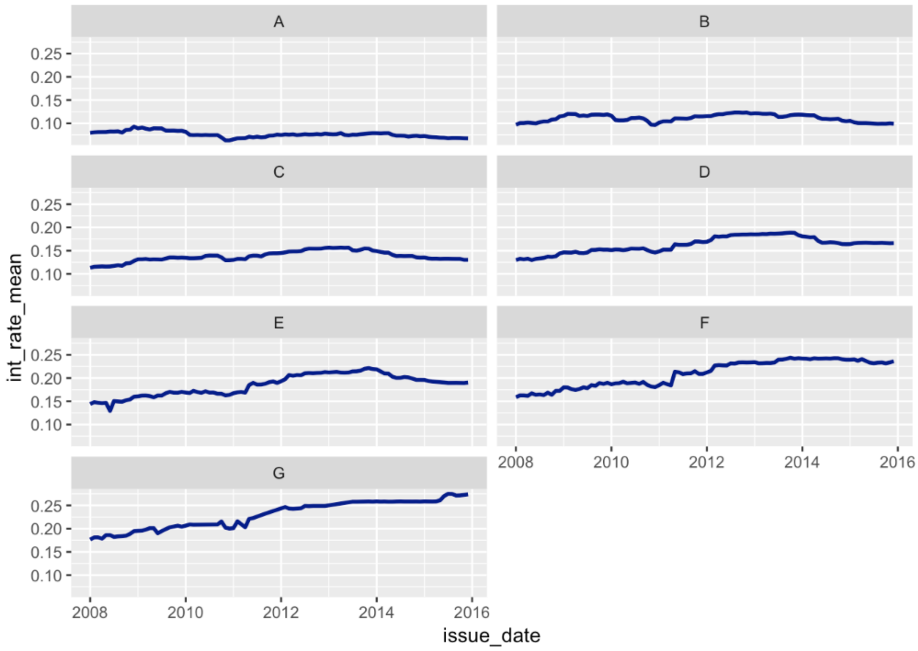


Boxplot: Loan Amount by Grade

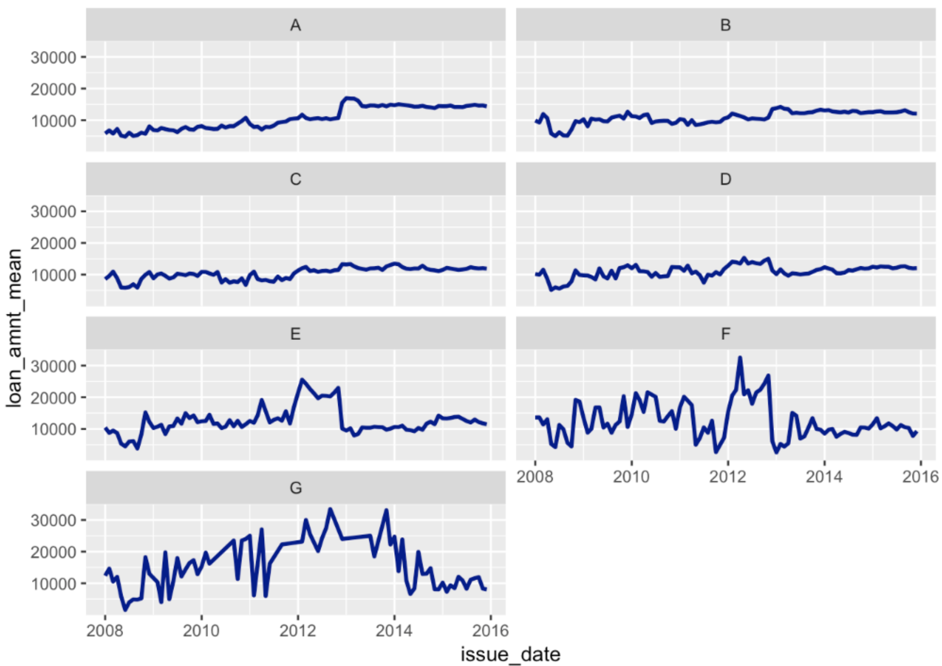


Boxplot: Home Ownership

A2.3 Trends of Interest Rates and Loan Amount



Development of Interest Rates Over Time



Development of Loan Amount Over Time

A3 Findings and Analysis

A3.1 Model 1

A3.1.1 Odds Ratios

Variable	Odds	Variable	Odds	Variable	Odds
Intercept	0.241	Purpose Education	1.670	Open account	1.016
Loan amount	1.000	Purpose Home improvment	1.056	Public record	1.094
Grade B	1.960	Purpose Vacation	1.053	Revolving balance	0.100
Grade C	3.087	Purpose House	1.090	Delinq 2 years	1.047
Grade D	4.077	Purpose Major purchase	0.982	Total Accounts	0.995
Grade E	5.056	Purpose Medical	1.097	Initial list status W	1.017
Grade F	6.180	Purpose Moving	1.076	Tax liens	0.951
Grade G	7.390	Purpose Other	0.939	inq last 6 mths	1.102
Home ownership Own	1.161	Purpose Renewable energy	1.227	Emp. length 1-3	0.940
Home ownership Rent	1.304	Purpose Small business	1.503	Emp. length 4-6	0.954
VS Source verified	1.119	Purpose Wedding	0.827	Emp. length 7-9	0.953
VS Verified	1.066	Dti	1.017	Emp. length 10+	0.973
Purpose Debt Consolidation	1.036	Annual Income	1.000	Emp. length missing	1.471
Purpose Card	0.981	Years of credit history	0.994		

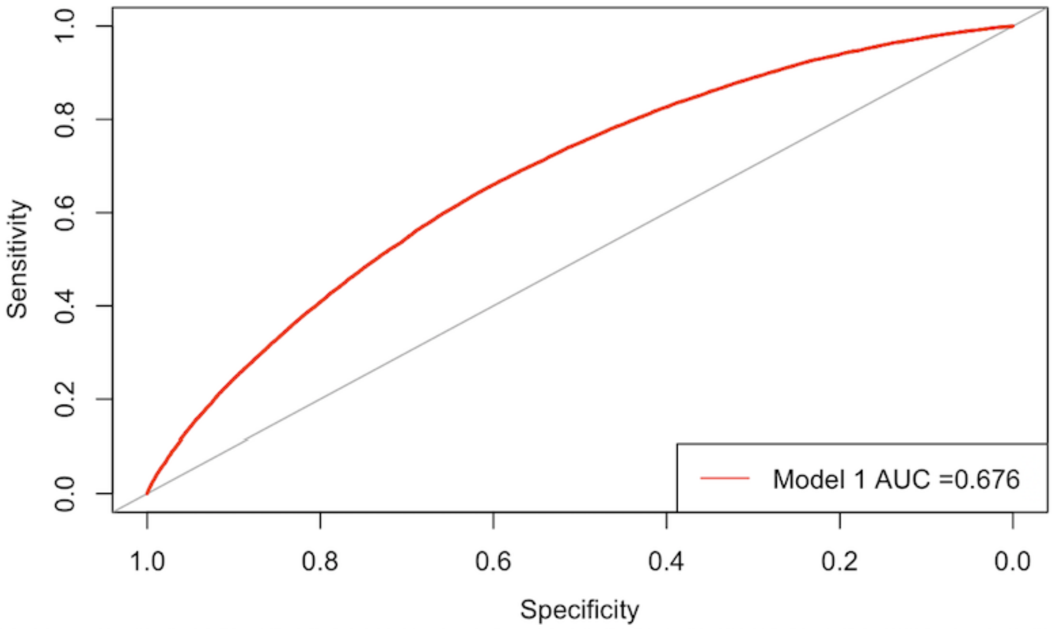
Odds Ratios Model 1

A3.1.2 Confusion Matrix

	Lasso			**Stepwise Selection**		
		Non-Default	Default		Non-Default	Default
Unbalanced	Non-Default	158,938	25,733	Non-Default	158,922	25,723
	Default	0	1	Default	16	11
		Non-Default	Default		Non-Default	Default
Undersampled	Non-Default	96,483	8,997	Non-Default	95,114	8,714
	Default	62,455	16,737	Default	63,824	17,020
		Non-Default	Default		Non-Default	Default
Oversampled	Non-Default	96,280	8,997	Non-Default	95,521	8,754
	Default	62,658	16,799	Default	63,417	16,980
		Non-Default	Default		Non-Default	Default
Both	Non-Default	96,379	8,918	Non-Default	95,625	8,771
	Default	62,559	16,816	Default	63,313	16,693
		Non-Default	Default		Non-Default	Default
ROSE	Non-Default	97,021	9,069	Non-Default	96,041	8,858
	Default	61,917	16,665	Default	62,897	16,876

Confusion Matrix: Model Specifications Part I

A3.1.3 ROC Curve



ROC Curve and AUC of Model 1

A3.1.4 Coefficient Estimates

```
Call:
glm(formula = loan_status ~ ., family = binomial(link = "logit"),
    data = undersampled.data, control = list(maxit = 1000))

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.1212  -1.1005   0.5361   1.0660   2.7054



Coefficients:
                                        Estimate    Std. Error z value
(Intercept)                        -1.4247771306  0.0691946130 -20.591
loan_amnt                           0.0000087830  0.0000009738   9.019
gradeB                              0.6730600357  0.0194908309  34.532
gradeC                              1.1274984067  0.0204067893  55.251
gradeD                              1.4057156658  0.0238671597  58.897
gradeE                              1.6210295231  0.0345883786  46.866
gradeF                              1.8217610051  0.0680780154  26.760
gradeG                              2.0005230579  0.1740666022  11.493
home_ownershipOWN                   0.1495330809  0.0212312763   7.043
home_ownershipRENT                  0.2656674934  0.0139211196  19.084
annual_inc                         -0.0000020970  0.0000001813 -11.568
verification_statusSource Verified  0.1129228339  0.0151534567   7.452
verification_statusVerified         0.0636855309  0.0164497185   3.872
purposecredit_card                 -0.0195110866  0.0622591050  -0.313
purposedebt_consolidation           0.0355629764  0.0614388958   0.579
purposeeducational                  0.5127246880  0.2609027333   1.965
purposehome_improvement             0.0540719663  0.0664113926   0.814
purposehouse                        0.0854697463  0.1101077989   0.776
purposemajor_purchase              -0.0183610657  0.0745619752  -0.246
purposemedical                      0.0923994425  0.0822018395   1.124
purposemoving                       0.0735233153  0.0895156293   0.821
purposeother                       -0.0626435303  0.0658072752  -0.952
purposerenewable_energy             0.2036946853  0.2126263987   0.958
purposesmall_business               0.4072891992  0.0803067874   5.072
purposevacation                     0.0513179453  0.0937798679   0.547
purposewedding                     -0.1900103741  0.1340303595  -1.418
dti                                 0.0172992028  0.0008385644  20.630
delinq_2yrs                         0.0469912549  0.0070736598   6.643
years_of_cr_history                -0.0062311563  0.0009176959  -6.790
inq_last_6mths                      0.0966500007  0.0061860385  15.624
open_acc                            0.0162121360  0.0016629190   9.749
pub_rec                             0.0900458211  0.0144462438   6.233
revol_bal                          -0.0000020841  0.0000003996  -5.215
total_acc                          -0.0045089780  0.0007712231  -5.847
initial_list_statusw                0.0171972761  0.0124891564   1.377
acc_now_delinq                     -0.0661906854  0.0785068919  -0.843
delinq_amnt                         0.0000027027  0.0000095644   0.283
tax_liens                          -0.0498820026  0.0224263991  -2.224
emp_length1-3                      -0.0616637095  0.0241896848  -2.549
emp_length10+                      -0.0483096951  0.0240760130  -2.007
emp_length4-6                      -0.0468800423  0.0254550252  -1.842
emp_length7-9                      -0.0278636273  0.0266408824  -1.046
emp_lengthmissing                   0.3861222173  0.0329991030  11.701
```

Coefficients Model 1

A3.1.5 Marginal Effects

```
Call:
logitmfx(formula = undersampled.model, data = undersampled.data)

Marginal Effects:
                                           dF/dx        Std. Err.
loan_amnt                             0.000002195745  0.000000243450
gradeB                                0.166098050554  0.004690702870
gradeC                                0.271305006838  0.004562984218
gradeD                                0.321210617862  0.004582542390
gradeE                                0.344199942053  0.005269703499
gradeF                                0.363891689922  0.008429052673
gradeG                                0.381957326710  0.018433822945
home_ownershipOWN                     0.037337502853  0.005287768914
home_ownershipRENT                    0.066318979638  0.003464873824
annual_inc                           -0.000000524254  0.000000045321
verification_statusSource Verified    0.028222157341  0.003784831551
verification_statusVerified           0.015919813380  0.004111151291
purposecredit_card                   -0.004877625647  0.015563674645
purposedebt_consolidation             0.008890406221  0.015358185097
purposeeducational                    0.125513300118  0.061189362942
purposehome_improvement               0.013515811948  0.016594145269
purposehouse                          0.021356359718  0.027482026330
purposemajor_purchase                -0.004590044235  0.018638273016
purposemedical                        0.023086041088  0.020511893263
purposemoving                         0.018374037415  0.022352658391
purposeother                         -0.015655668761  0.016436451916
purposerenewable_energy               0.050759018944  0.052631903547
purposesmall_business                 0.100537069571  0.019316570142
purposevacation                       0.012827336414  0.023432175218
purposewedding                       -0.047352070326  0.033196517607
dti                                   0.004324782956  0.000209640644
delinq_2yrs                           0.011747765492  0.001768407913
years_of_cr_history                  -0.001557782674  0.000229423056
inq_last_6mths                        0.024162400992  0.001546505723
open_acc                              0.004053017361  0.000415728001
pub_rec                               0.022511362861  0.003611547361
revol_bal                            -0.000000521015  0.000000099909
total_acc                            -0.001127239874  0.000192805004
initial_list_statusw                  0.004299283490  0.003122230036
acc_now_delinq                       -0.016547603428  0.019626642540
delinq_amnt                           0.000000675660  0.000002391094
tax_liens                            -0.012470449453  0.005606577079
emp_length1-3                        -0.015413170628  0.006044422349
emp_length10+                        -0.012076246255  0.006017413488
emp_length4-6                        -0.011718374269  0.006361341224
emp_length7-9                        -0.006965442792  0.006659081383
emp_lengthmissing                     0.095609016131  0.008012492642
```

Marginal Effects Model 1

A3.2 Model 2

A3.2.1 Full Regression Output

	Loan Status				
Predictors	*Estimate*	*df/dx*	*Std.Err*	*p*	
(Intercept)	-1.41	-	-	**<0.001**	***
loan_amnt	0.00	0.00	(0.00)	**<0.001**	***
grade B	0.67	0.17	(0.00)	**<0.001**	***
grade C	1.13	0.27	(0.00)	**<0.001**	***
grade D	1.41	0.32	(0.00)	**<0.001**	***
grade E	1.63	0.35	(0.01)	**<0.001**	***
grade F	1.83	0.37	(0.01)	**<0.001**	***
grade G	1.98	0.38	(0.02)	**<0.001**	***
home_ownership Own	1.15	0.04	(0.01)	**<0.001**	***
home_ownership Rent	0.27	0.07	(0.00)	**<0.001**	***
annual_inc	-0.00	-0.00	(0.00)	**<0.001**	***
verification_status Source Verified	0.11	0.03	(0.00)	**<0.001**	***
verification_status Verified	0.06	0.01	(0.00)	**<0.001**	***
purpose credit card	-0.01	-0.00	(0.02)	0.846	
purpose debt consolidation	0.04	0.01	(0.02)	0.490	
purpose educational	0.45	0.11	(0.06)	0.080	
purpose home improvement	0.06	0.01	(0.02)	0.380	
purpose house	0.09	0.02	(0.03)	0.428	
purpose major purchase	-0.01	-0.00	(0.02)	0.838	
purpose medical	0.10	0.02	(0.02)	0.248	
purpose moving	0.08	0.02	(0.02)	0.377	
purpose other	-0.06	-0.01	(0.02)	0.363	
purpose renewable energy	0.20	0.05	(0.05)	0.346	
purpose small business	0.40	0.10	(0.02)	**<0.001**	***
purpose vacation	0.06	0.01	(0.02)	0.530	
purpose wedding	-0.20	-0.05	(0.03)	0.144	
dti	0.02	0.00	(0.00)	**<0.001**	***
delinq_2yrs	0.05	0.01	(0.00)	**<0.001**	***
years_of_cr_history	-0.01	-0.00	(0.00)	**<0.001**	***
inq_last_6mths	0.10	0.02	(0.00)	**<0.001**	***
open_acc	0.02	0.00	(0.00)	**<0.001**	***
pub_rec	0.09	0.02	(0.00)	**<0.001**	***
revol_bal	-0.00	-0.00	(0.00)	**<0.001**	***
total_acc	-0.00	-0.00	(0.00)	**<0.001**	***
initial_list_statusw	0.01	0.00	(0.00)	0.298	
acc_now_delinq	-0.06	-0.02	(0.02)	0.414	
delinq_amnt	0.00	0.00	(0.00)	0.797	
tax_liens	-0.05	-0.01	(0.01)	**<0.021**	*
gdp_growth	-0.02	-0.00	(0.00)	0.206	
unemployment_growth	0.77	0.19	(0.03)	**<0.001**	***
emp_length1-3	-0.06	-0.02	(0.01)	**0.012**	*
emp_length 10+	-0.05	-0.01	(0.01)	0.058	
emp_length 4-6	-0.05	-0.01	(0.01)	0.071	
emp_length 7-9	-0.02	-0.01	(0.01)	0.364	
emp_length missing	0.38	0.10	(0.01)	**<0.001**	***

Regression Output Model 2

A3.2.2 Coefficient Estimates

```
Call:
glm(formula = loan_status ~ ., family = binomial(link = "logit"),
    data = undersampled.data.macro, control = list(maxit = 1000))

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.1496  -1.1000   0.5286   1.0664   2.7389



Coefficients:
                                    Estimate   Std. Error z value
(Intercept)                    -1.4077144559 0.0695504409 -20.240
loan_amnt                       0.0000088953 0.0000009743   9.130
gradeB                          0.6740347023 0.0194970337  34.571
gradeC                          1.1316769391 0.0204250250  55.406
gradeD                          1.4122214965 0.0238960352  59.099
gradeE                          1.6298768345 0.0346252594  47.072
gradeF                          1.8313464859 0.0681089748  26.888
gradeG                          1.9864215386 0.1740354827  11.414
home_ownershipOWN               0.1481815917 0.0212376934   6.977
home_ownershipRENT              0.2655427084 0.0139251768  19.069
annual_inc                     -0.0000021070 0.0000001814 -11.618
verification_statusSource Verified  0.1095942636 0.0151642742   7.227
verification_statusVerified     0.0574786130 0.0164978562   3.484
purposecredit_card             -0.0121245745 0.0622763262  -0.195
purposedebt_consolidation       0.0424579378 0.0614540173   0.691
purposeeducational              0.4574520882 0.2613153382   1.751
purposehome_improvement         0.0582789472 0.0664215462   0.877
purposehouse                    0.0873517827 0.1100952111   0.793
purposemajor_purchase          -0.0152408301 0.0745711444  -0.204
purposemedical                  0.0948884822 0.0822058342   1.154
purposemoving                   0.0790380465 0.0895018784   0.883
purposeother                   -0.0598748904 0.0658117070  -0.910
purposerenewable_energy         0.2001121543 0.2123992636   0.942
purposesmall_business           0.4023343267 0.0802881884   5.011
purposevacation                 0.0588874447 0.0937718401   0.628
purposewedding                 -0.1959411200 0.1340002841  -1.462
dti                             0.0173017482 0.0008387409  20.628
delinq_2yrs                     0.0468498116 0.0070757605   6.621
years_of_cr_history            -0.0061745344 0.0009178326  -6.727
inq_last_6mths                  0.0959428599 0.0061911430  15.497
open_acc                        0.0161459719 0.0016633715   9.707
pub_rec                         0.0914751811 0.0144530712   6.329
revol_bal                      -0.0000021247 0.0000004004  -5.306
total_acc                      -0.0043771113 0.0007716948  -5.672
initial_list_statusw            0.0130106630 0.0125080299   1.040
acc_now_delinq                 -0.0642065810 0.0785415623  -0.817
delinq_amnt                     0.0000024593 0.0000095671   0.257
tax_liens                      -0.0516160760 0.0224248090  -2.302
gdp_growth                     -0.0181931874 0.0143749996  -1.266
unemployment_growth             0.7671551978 0.1370617856   5.597
emp_length1-3                  -0.0607125024 0.0241954861  -2.509
emp_length10+                  -0.0456584961 0.0240845091  -1.896
emp_length4-6                  -0.0459423033 0.0254603408  -1.804
emp_length7-9                  -0.0242000190 0.0266531038  -0.908
emp_lengthmissing               0.3890436737 0.0330097879  11.786
```

Coefficients Model 2

A3.2.3 Marginal Effects

```
Call:
logitmfx(formula = undersampled.model.macro, data = undersampled.data.macro)

Marginal Effects:
                                        dF/dx      Std. Err.         z
loan_amnt                       0.00000222382 0.00000024357    9.1302
gradeB                          0.16633250078 0.00469168807   35.4526
gradeC                          0.27223611344 0.00456342626   59.6561
gradeD                          0.32244960403 0.00457788186   70.4364
gradeE                          0.34553449895 0.00525010569   65.8148
gradeF                          0.36507205644 0.00837800155   43.5751
gradeG                          0.38045927755 0.01862715977   20.4250
home_ownershipOWN               0.03700091123 0.00528974216    6.9948
home_ownershipRENT              0.06628792390 0.00346589855   19.1258
annual_inc                     -0.00000052676 0.00000004534  -11.6179
verification_statusSource Verified  0.02739077040 0.00378774570    7.2314
verification_statusVerified     0.01436851879 0.00412343399    3.4846
purposecredit_card             -0.00303109308 0.01556853645   -0.1947
purposedebt_consolidation       0.01061394124 0.01536137604    0.6909
purposeeducational              0.11246411465 0.06208935997    1.8113
purposehome_improvement         0.01456696040 0.01659515709    0.8778
purposehouse                    0.02182608956 0.02747680313    0.7943
purposemajor_purchase          -0.00381006566 0.01864113540   -0.2044
purposemedical                  0.02370710752 0.02051070184    1.1558
purposemoving                   0.01975097647 0.02234490707    0.8839
purposeother                   -0.01496412565 0.01643879585   -0.9103
purposerenewable_energy         0.04987210621 0.05259428299    0.9482
purposesmall_business           0.09934482822 0.01933025718    5.1393
purposevacation                 0.01471850723 0.02342575369    0.6283
purposewedding                 -0.04882053174 0.03316984855   -1.4718
dti                             0.00432541917 0.00020968477   20.6282
delinq_2yrs                     0.01171240446 0.00176893306    6.6212
years_of_cr_history            -0.00154362721 0.00022945724   -6.7273
inq_last_6mths                  0.02398561578 0.00154778183   15.4968
open_acc                        0.00403647629 0.00041584109    9.7068
pub_rec                         0.02286870069 0.00361325413    6.3291
revol_bal                      -0.00000053117 0.00000010010   -5.3062
total_acc                      -0.00109427331 0.00019292294   -5.6721
initial_list_statusw            0.00325264598 0.00312697076    1.0402
acc_now_delinq                 -0.01605157887 0.01963530951   -0.8175
delinq_amnt                     0.00000061483 0.00000239175    0.2571
tax_liens                      -0.01290396563 0.00560617941   -2.3017
gdp_growth                     -0.00454827804 0.00359373505   -1.2656
unemployment_growth             0.19178800630 0.03426530344    5.5971
emp_length1-3                  -0.01517548286 0.00604595546   -2.5100
emp_length10+                  -0.01141361184 0.00601969048   -1.8960
emp_length4-6                  -0.01148402526 0.00636275489   -1.8049
emp_length7-9                  -0.00604967984 0.00666237710   -0.9080
emp_lengthmissing               0.09631836168 0.00801154127   12.0225
```

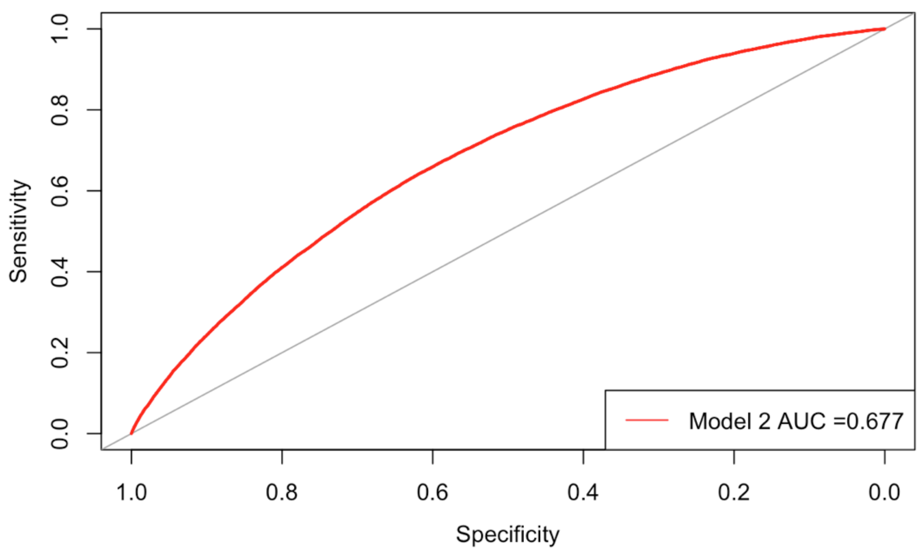
Marginal Effects Model 2

A3.2.4 Confusion Matrix

	Lasso			Stepwise Selection		
		Non-Default	Default		Non-Default	Default
Model 2	Non-Default	97,209	9,122	Non-Default	95,238	8,723
	Default	61,729	16,612	Default	63,700	17,011

Confusion Matrix: Model Specifications Part II

A3.2.5 ROC Curve



ROC Curve and AUC of Model 2

A3.3 Model Comparison

	Pseudo-R^2
Model 1	0.0951
Model 2	0.0954
Grades	0.0771

Pseudo R-Squared

```
Likelihood ratio test

Model 1: loan_status ~ loan_amnt + grade + home_ownership + annual_inc +
    verification_status + purpose + dti + delinq_2yrs + years_of_cr_history +
    inq_last_6mths + open_acc + pub_rec + revol_bal + total_acc +
    initial_list_status + acc_now_delinq + delinq_amnt + tax_liens +
    emp_length
Model 2: loan_status ~ loan_amnt + grade + home_ownership + annual_inc +
    verification_status + purpose + dti + delinq_2yrs + years_of_cr_history +
    inq_last_6mths + open_acc + pub_rec + revol_bal + total_acc +
    initial_list_status + acc_now_delinq + delinq_amnt + tax_liens +
    gdp_growth + unemployment_growth + emp_length
  #Df LogLik Df  Chisq     Pr(>Chisq)
1  43 -77177
2  45 -77156  2 40.407 0.000000001682 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Likelihood Ratio Test: Model 1 and Model 2

```
Likelihood ratio test

Model 1: loan_status ~ loan_amnt + grade + home_ownership + annual_inc +
    verification_status + purpose + dti + delinq_2yrs + years_of_cr_history +
    inq_last_6mths + open_acc + pub_rec + revol_bal + total_acc +
    initial_list_status + acc_now_delinq + delinq_amnt + tax_liens +
    unemployment_growth + emp_length
Model 2: loan_status ~ grade
  #Df LogLik  Df  Chisq            Pr(>Chisq)
1  44 -77157
2   7 -78355 -37 2396.6 < 0.00000000000000022 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Likelihood Ratio Test: Model 2 and Grades

A3.4 Expected Return Alternative Calculation

$$E[r_p] = E[p(y=1) * i + (1 - p(y=1)) * \frac{it}{36}] \tag{26}$$

where $P(D=1)$ is the probability of default, t is the month of default (1-36), i is the interest rate and 36 is the maturity of the loan. Loan defaults on LendingClub's platform are assumed to be independent of each other, as one loan default does not directly cause another loan default. Further, the time a loan can default is fixed in our study. Thus, following the Poisson distribution, the historical default rates of each grade for $P(D=1)$ are used (Table 3, Section 6.2). The Poisson distribution an its mean are is given by:

$$P(X=x) = \frac{\lambda^x e^{-\lambda}}{x!} \tag{27}$$

$$E[X] = Var(X) = \lambda \tag{28}$$

Where λ is the default rate, X is the number of defaults in the time period and x is a defaulted loan. Further, the expected loss is accounted for using LGD and recovery rate.