Empirical Assignment in Seminar Topics in Fintech

Prediction of Borrower Default Risk

Group 4

ERASMUS
UNIVERSITEIT
ROTTERDAM

Date: 21/04/2022

Ludwig Baunach (621956)

Frederico [redacted]

Priyanka [redacted]

Jonas [redacted]

Jacques [redacted]

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1. Abstract

The power to predict default by their client is something that Fintech and banks have been trying to achieve for a long time. Asymmetric information between borrowers and lenders has a great effect in the banking market and to reduce this gap, banks and FinTechs commonly analyse hard information about their borrowers to predict loan risk and the risk of default. Recently new approaches to better predict loan risk are being used with the complementation of soft information. Bandora has its own credit rating, and has its data open to access. This study tried to use soft information inside Bandora`s data to check if soft information improves the default prediction of Bandora`s credit system or can replace it entirely. The variables Date and time, Duration and Early Repayment were used as behavioural traits in the log-regression tenfold cross validation (10x CV). To test whether our model adds discriminatory power to the Bondora rating model, we use the area under the curve (AUC). The introduction of the behavioural variables did not have a better result than Bandora`s credit system but when combined to it increases the AUC by 1 percentage point. Therefore, Behavioural variables (habits) do complement rather than substitute credit scores for predicting default risk.

2. Introduction

Accurate prediction of borrower default risk has been a central objective in banking business ever since. Before issuing a credit, financial institutions analyse various risk types to determine worthiness and required securities and interest rate. As a contrast to changes in the economic environment, which affect systemic and market risk, default risk describes the situation when a borrower fails to pay back its debts. Hence, banks face a challenge to decide which information provides insights on likeliness to default. Over decades, this data has been limited to micro-level financial and personal information and macro-level trends, such as past income fluctuations, savings, consumption, and interest rates (Arellano, 2008). With the rise of data availability in the Digital Age, the information gap between borrower and lender is decreasing. While data on a borrower's accounts or address has been essential before, financial institutions assess data on a whole new level including the analysis of characteristics, risk behaviour and other soft factors collected from online user activities. The cornucopia of accessible consumer information of its online behaviour is summarized in the term digital footprint reaching, which reaches from login frequency to complex characteristics (Deeva, 2019). Therefore, we need to ask whether models including the digital footprint can outperform conventional models in predicting borrower default risk.

While using utility functions as an abstract method of calculating individual preferences in microeconomics, modern data capturing methods can create individual functions incorporating consumer behaviours and characteristics. One significant role in consumer theory is the preference of time. Decisions in saving, investing, and consuming are always made by considering various variables, but the most important dimension remains time (von Böhm-Bawerk, 1889). Individuals assess the current situation and value benefits, downsides, and risks about the future to decide what is optimal to do now. Famous examples from academic theory draw the literary entanglement of Robinson Crusoe on his lonely island to decide over fruit consumption now and tomorrow. When introducing the far more complicated human biases, behavioural errors, and inconsistencies to the example, we quickly drop main assumptions of rationality, constant preferences, and consistency. An important bias is the concept of dynamic inconsistency, which describes that, individuals act opposingly at different time frames. Rationally, when an individual prefers option A over B and B over C, he should also prefer A over C. However, this logical argumentation often is not the case. This can partly be explained by time preferences and seeking variety, such that an individual does not always prefer his favourite restaurant over alternatives. The more promising explanations rely on psychological factors, which prevent individuals from acting according to optimal or earlier-taken decisions. Plans have been made to finish a task, but procrastination and distraction hinder the completion.

Hyperbolic discounting is another bias to describe inconsistencies in preferences. It describes a scenario, in which individuals tend to receive benefits earlier and costs later with regards to time (Loewenstein and Thaler, 1989). There are many current examples from COVID19 for hyperbolic discounting, such that people are not willing to pay the costs of preventive health care (e.g., vaccinations) in terms of taking waiting time. On the other hand, the picture entirely changes when regarding benefits. Individuals prefer to receive benefits sooner than later, which also is manipulated by companies to offer expensive consumption goods, such as flatscreens, phones or sport cars, for free at time of buying, but with overpriced interest rates and repayments. Hereby, time has another important implication, namely characteristics like self-reflection, consideration, and weighing between costs and benefits. While those characteristics remained unseen for past decades, the assessment of large consumer data creates the possibility to incorporate the degree of time consistency, hyperbolic discounting, and the awareness of these biases into a new degree of visibility. If determining individual time preferences and characteristics is possible, which implications do they have in financial aspects?

Banks incorporated both technology and business trends to make their services effective and efficient. For example, computers and the internet were invented for mathematical-scientific and military purposes, respectively, which were later introduced to banks as well as to other businesses. The significant differences in the ongoing FinTech revolution rely on the omission of banking intermediaries, the lack of regulation, the use of decentralized networks and the overall rise of data availability. While earlier developments changed certain services and procedures in banking, FinTech has a chance of disrupting the whole industry by excessive innovation creation (Wewege and Thomsett, 2019). However, the next technological revolution in finance is on the verge of realization: TechFin. As financial technology companies (FinTech) created software solutions for financial companies, technical finance companies rose from different fields of consumer technology, which turned towards providing financial services. The TechFin companies, such as Google, Amazon, Facebook, and Apple, uphold massive amounts of consumer data as their main assets to be used potentially for risk models. To prevent future discrimination and favouritism in algorithms, it is incredibly important to describe, analyse, and discuss characteristics and behaviours data in financial models. From a banking perspective, it is furthermore relevant to understand what variables could outperform conventional variables as substitutes or complements. In the following empirical study, we analyse how soft information on consumer behaviour improves conventional financial models on borrower default risk. Therefore, we specifically test whether time variables such as duration, weekday, day, and time as well as early repayments have explanatory power to predict borrower default risk as good or better than conventional models. This discussion follows the analysis of Berg, Burg, Gombovic, and Puri (2020) regarding discriminatory effects of time variables.

3. Literature Review

Use of soft information as an advantage

One crucial point in debt and banking literature is information asymmetries. It has been even in the focus points in securities regulators (Loss, 1998). Stiglitz and Weiss (1981) showed how asymmetric information between borrowers and lenders can influence the market equilibrium. Hard information is more commonly used for banks to predict the loans risk and their risk of default, and they are effective. Edelberg (2006) proved that the use of the data from the Survey of Consumer Finances helped to calculate the default risk. However, soft information has been used for banking literacy to help identifying the default rate of borrowers and to reduce moral hazard, so it can be also used to reduce asymmetric information (Liberti and Petersen, 2017; Berger, Miller, Petersen, Rajan, and Stein, 2005).

To reduce the information gap between lenders and borrowers Einav, Jenkins, and Levin (2013) attempted a study to check if credit score systems could help with this problem. With a model used in the loan market for car deals, they found that the use of the credit score system increased the profits for auto finance companies. The same evidence, but in a different context, was also found by other authors (Petersen and Rajan, 2002; Akhavein, Frame and White, 2005).

Jiang, Wang, Wang, and Ding (2018) extended the existing credit rating methods in their analysis, adding hard and soft information from borrowers in a P2P platform. They proposed a model that analysed descriptive text in the loan applications and the traditional hard information. They found that soft information used helps identifying borrowers, having a significant ability in discriminating loan defaults. They also say that the use of those soft information can be integrated with default prediction models to improve the model's performance and decrease the risk of default.

Berg, Burg, Gombović and Puri (2020) used easily accessible variables from a digital footprint and combined that information with the credit bureau scores to predict consumer's default. In this study the authors found several pieces of information that helps to predict default. Aligned with the studies presented before the hour of application can be an important tool to measure the risk of default. Customers that realized purchases between midnight and 6 a.m. were twice as likely to default than customers purchasing between noon and 6 p.m.

In accordance with the result from Berg, Burg, Gombović and Puri (2020) and the previous studies presented, we came up with the hypothesis that people who purchase between midnight and 6 a.m. are likely to suffer from some sleep deprivation, thus they have an increase in impulsivity, tiredness, and other consequences, wherefore they are likely to have a higher risk to default.

The work presented earlier influenced our choice to check whether we could improve Bandora's rating system using soft information inside Bandora's data. The soft information available and useful for a statistics analysis were *Date and time, duration,* and *early repayment*.

Date and time are variables of the date and time of the start of the application. They can relate to habits that have been reported in past literature, such as impulsivity, sleep deprivation and fatigue. *Duration* measures the time between the application started and the hour the loan was listed. This variable is used as a proxy to motivation, where people that finished their application earlier are more motivated. There is a lack of information about *early repayment* as a predictor of default in the current literature, however, we still think that this variable represents a personal characteristic associated with willingness to pay.

Impulsivity in psychology and economics

According to rational economic models the average person tends to make loans in the beginning of their professional life in order to increase his utility and to anticipate spending, with the expectation that his income is going to increase. The rational model predicts that a person in the beginning of their professional life has low earnings and as the time passes the earnings increase. People expect to make more money in the future when they start their career and therefore, they finance assets that increase utilization above current financial levels. Before retirement, people add to their savings to prepare for retirement when their expenses increase and surpass their earnings. In these economic scenarios, the "rational" people act to maximize their utility based on time-consistent preferences. (Bagliano and Bertola, 2004)

However, people do not behave according to "rational" premise. People tend to systematically overvalue immediate costs and benefits and undervalue them in the future. That is, they do not have time-consistent preferences as the traditional economic models think, and people give more importance to events in the present than events in the future (Franken et al., 2008). In psychology this kind of behaviour is defined as impulsivity. People that are highly impulsive tend to seek immediate rewards as they estimate their choices and ignore the negative consequences of them (Martin and Potts, 2009).

Impulsivity in debt and default (lack of self-control)

Impulsive behaviour and lack of self-control have been linked with impulsive buying and increase of debt in the literature. Webley and Nyhus (2001) made a study linking self-control and indebtedness. They used four indices to measure self-control spending style, obesity, smoking and drinking. The authors concluded that all the four measures are linked with getting in debt and that people that have a lack of self-control are more likely to get in debt and would not be able to pay it.

Ottaviani and Vandone (2011) did research in the relationship of household indebtedness and impulsiveness. The authors used a Probit model to estimate the role of emotional factors in determining household participation in the debt market. They did the research for unsecured and secured debt. The results for them were different, for secured debt impulsive behaviours did not show any significant influence, however impulsive behaviour can be a great predictor for unsecured debt. People with unsecured debt are more likely to make impulsive decisions and are more likely to run into indebtedness. Anderloni et al. (2012) and Gathergood (2012) did different studies with similar conclusions. Both studies realized an empirical analysis that indicates a relation between impulsivity and over-indebtedness or financial fragility.

McCarthy (2011) did research to check if people with a good financial education could overcome impulsivity. The author found that even for financially literate people, impulsive people are more likely to get into financial problems. Ladas et al. (2014) went a step further and found out that the strongest predictor of indebtedness by consumers is impulsiveness.

Strömbäck et al. (2017) made a study to find if self-control has a positive effect on savings behaviour. The findings have shown that the hypothesis was right but also that people with good self-control suffer less from financial matters and are more secure and confident in their future financial situation. People with good self-control were also less likely to get into indebtedness due to their financial behaviours of decision makers.

Sleep deprivation, impulsivity, and fatigue

Impulsivity has shown to be a great influence in getting in debt and defaulting. *Date and time* are variables that can represent impulsivity and fatigue. It is reasonable to think that people that start their application between midnight and 6 a.m. suffer from sleep deprivation and there are many studies that link sleep deprivation with fatigue and impulsivity.

Impulsive behaviour has been associated with sleep deprivation. Romer (2010) was able to link restricted sleep for young adults with impulsive behaviour. The author said that young adults that experience lack of sleep do not develop their brain as they were supposed to and this can impact the person's life, being the increase in impulsivity is one of the effects of sleep deprivation.

Anderson and Platten (2011) found out that one night of sleep loss leads to increased impulsivity. Yoo et al. (2008) have also found that sleep deprivation leads to increase in impulsivity, but it was for a longer period of less sleep than advised and not for a whole night awake. Tashjian et al. (2017) made an experiment tracking the quality of sleep for different adolescents, but also controlling for personal traits. The authors found out that a poor quality of sleep increases impulsiveness.

Those studies were more related to a longer period of sleep deprivation or a whole night awake. Rossa et al. (2014) made a study in young adults that tried to measure if restricted sleep increases impulsive behaviours. The result for this shorter period of restricted sleep is similar with the other studies and highlights the increase in impulsive behaviour and potentially high-risk behaviour for young adults in restricted sleep.

Mulette-Gillman et al. (2015) conducted a study on the effects of fatigue in behaviour and decision making. They used a control and treatment group, where the treatment group had to do taxing cognitive activities for 60- 90 minutes and the control group had to watch relaxing videos. The results showed that cognitive fatigue destabilizes economic decision making, resulting in inconsistent preferences and informational strategies that may significantly reduce decision quality.

When awake time exceeds 16 hours, most begin to show a significant reduction in reaction time (RT) and a decrease in score accuracy on tests of psychomotor vigilance and this decline trend lasts all night until the early hours of the morning (Goel et al., 2009).

When people suffer from sleep deprivation, they may change their normal functional activity of brain networks that affects the evaluation of rewards and punishments. This leads to change in risk judgements that favour unrealistic expectations of gains and underestimation of the loss's consequence (Venkatraman et al., 2007).

4. Research Question

Based on the literature in the field as well as the insights from the paper of Berg et al. (2020), we created a model that predicts default risk based on soft information or behaviours treats, which we will define as habits. We perform our research in a comparable manner to the digital footprint paper (Berg et al., 2020). Instead of using information derived from the digital footprint as predictor of default, we will use habits, or information derived from soft factors/ behaviours treats as a predictor of default. Hence, our research question becomes:

Do habits (information derived from soft information and behaviours treats) complement rather than substitute for credit score information to predict default risk?

The research question is relevant because the implications of the results could improve predicting default risk. Namely, if habits complement credit score information, a lender that uses information from both sources (credit scores plus habits) will make superior lending decisions, compared to lenders that will only access one of the two sources of information. Berg et al. (2020) found evidence that the time of the day a customer applies for a loan increases the discriminatory power of their model. The main goal of this research is to discuss economics and behavioural mechanisms that can explain this effect as well as test whether the behavioural related variables can successfully increase the accuracy in predicting distress rates of peer-to-peer loans on Bondora's website. Distress rate is defined as a late payment status in the loan history.

5. Data

Source

The data we have used in this research is derived from Bondora. Bondora has several public reports, and we have used the "Loan Dataset". A list with the definitions of variables that are used in the dataset is given on the Bondora website (Bondora, 2022a)

"Bondora earns its revenue from financing and servicing customers' loans, and the revenue is sourced from five services: (1) Contract fees charged to borrowers once the principal amount of their loan is issued. (2) An annual management fee charged to borrowers throughout their loan repayment period. (3) B secure, a service that offers borrowers complete flexibility in managing their loan repayment schedules, in case they have a change in their personal financial circumstances. (4) Interest earned on unsold loan receivables. (5) Go and Grow withdrawal fees (€1 per withdrawal, no matter the account size). Note: Debt collection fees are also charged to borrowers where laws permit or are deducted from cash flow recovered from delinquent loans in the collection process. This essentially is not a revenue source of Bondora, but a way to cover the costs of recovery". (Bondora, 2022b)

Variables

Independent variable

We want to build a model that predicts default risk, where default risk is defined as "the probability that a borrower fails to make full and timely payments of principal and interest, according to the terms of the debt security involved" (CFI, 2022). So, when a borrower fails to make a timely payment (more than 60 days) Bondora has in its dataset a variable which prescribes a label LATE to a loan. We use this variable as proxy for financial distress or risk of default. This is thus our independent variable.

Dependent variables (behavior)

Date and time

We used the Bondora variable ApplicationStartedDate to create two new variables, one for the date and one for the time. The date variable (dummy variable) represents the day of the week (Monday to Sunday), while the time variable is a categorical variable that is divided into four blocks of six hours each (morning, noon, midday, night). The motivation to use the date and time variable is due to the results of Franken et al (2008) that people do not have time-consistent preferences. This implies hyperbolic discounting (valuing present more than future due to risk component) and could therefore be used as a measure for impulsivity. These findings are only strengthened by the results of the research of Ottoviani & Vandone (2011), namely that impulsive behaviour can be a great predictor for unsecured debt. Another motivation to include the time variable is due to the research of Anderson & Platten (2011) where one night of sleep deprivation leads to increased impulsivity.

Duration

Duration measures the time between Application started and loan listed in hour. The motivation to include the Duration variable is that we would expect that, given that Bondora uses the same amount of time for each loan application, the duration could capture how 'motivated' a loan applicant is, because the shorter the duration the stronger the motivation. The variable duration measures two factors. First, it measures the time it takes for Bondora to assess the loan and list it online. We assume that this process is on average the same among the different loans. Second, duration measures the time it takes for a borrower to complete the application. In our opinion, it is reasonable to assume that this factor is the main cause of variation and can be used as an indicator for behaviours.

Table 1 in the appendix mean, standard deviation, minimum and maximum of the variable duration across the different models. Model 3,4,5,6 and 99 have negative values. Moreover, the mean changes across the average. Since negative duration counts do not make sense, we decided to only use a model that has positive duration counts. We selected model 1 because of the highest observation counts.

Early repayments

The motivation for including Early Repayments is that, although we know the main motivation to pay early is the financial ability to pay early (ability), part of the action could also be explained through personal characteristics or soft information that represents the behaviour willingness to pay early (willingness). We ascribe willingness to behaviour motivation, and ability to financial motivation.

Dependent variables (Financial)

Rating

Bondora has used different models to calculate a loan's Rating (Bondora's own credit score). From 2013 through 2022 Bondora has changed their model 7 times (see table 4 in the appendix). Because we don't know how the model has changed, we assume that there could be major differences between the models. Therefore, we've made the decision to use three model versions: 1, 5 and 6 (based upon highest number of observations) and duplicate the dataset according to these three models' versions. Now, we have three identical datasets, where the only difference is the model version used to calculate a Rating for a loan. Then we checked the values of our dependent variables for all three model versions and found strange values for the Duration variable for model version 6, namely negative values. For model 5 we found strange value for UseofLoan, namely (-1). So, we ended with model 1 and 5 and used Duration instead of UseofLoan. However, when analyzing the descriptive statistics of the control variables, we saw a skewed distribution of Gender in model version 5 (see table 2 in appendix). Thus, our results are based upon model version 1.

Dependent variables (Control)

Age, Gender, Country, and Education. Give a summary of descriptive statistics. Highlight Gender distribution model 5.

Table 2 & 3 in the appendix shows the descriptive statistics of the control variables. For Age, Country, Gender and Education the descriptive statistics show us how these variables are distributed among the different datasets (Total, only model 1, only model 5). All control variables look fine, except for the Gender variable. When we zoom in on how gender is distributed in the dataset for model 5, we see a distribution of 87% male vs 9% female, which implies a skewed distribution. We want our research to focus on measuring the impact of our habit's variables on default risk. So, we decided it is better to leave model 5 out due to the skewed distribution and because otherwise it affects the unambiguity of our results. Therefore, our results are based upon model version 1.

Note on data manipulation - Cleaning

There are several variables which contain strange values. Some variables, such as (UseofLoan, Rating) have their definition changed over the years and so a change in value could be represented by a real change in value with the same definition or not a real change but a different definition, or both, so a real change and a different definition. Because Bondora does not give us insight in how these different values of the same variables should be interpreted, we decided to leave out time-related definition differences in our dataset and focus just on ratings derived from model version 1. We also wanted to consider the time between a borrower creating an account on Bondora and performing a loan application which is accepted, which is the Duration variable. The problem is that, although we thought that we found the variables representing these instances, Bondora could either have changed the definition over time or made a mistake. This is because we have found negative time between creating a Bondora account and the loan application, which does not make any sense.

So, the steps we took from the raw Bondora Loan Dataset to the kind of dataset we used for our statistical analysis are the following.

1. Select our variables from main dataset

2. Filter Observations without NA

3. Creating and collecting variables:

4. Create two Datasets: The only difference between these two datasets is the model version used by Bondora to realize a ‘credit score’. We decided to use model version 1.

6. Methodology

The methodology of our work is inspired by the work of Berg et al. (2020) about the discriminatory power of the digital footprint. The authors use a log-regression to predict default rates of loans issued by a big e-commerce company in Germany. We use a log-regression as well but do not use a single out of the sample test as our main robustness test. Instead, we use a tenfold cross validation (10x CV) to train our model. As pointed out by Luque-Fernandez et al. (2019) K-fold cross-validation can generate a more realistic estimate of predictive performance than classic single sample splits. The method works as follows. The data is split randomly into two parts. 90% of the data is used to train the model and the other 10% is used to test it. Thereafter, the averages of 10 iterations are taken to access the accuracy of the model. To test whether our model adds discriminatory power to the Bondora rating model, we use the area under the curve (AUC). The AUC is a measure to assess the accuracy of our model. As described in Berg et al. (2020), the AUC ranges from 50% (purely random / flicking a fair coin) to 100% (perfect prediction) and is a widely used metric to measure the accuracy of credit models. The AUC corresponds to the probability of successfully predicting a good case when faced with one random good and one random bad case (Hanley and McNeil, 1982). Based on research by Iyer et al. (2016) an AUC of 60% is generally considered desirable in information-scarce environments, whereas AUCs of 70% or greater are the goal in information-rich environments.

Our model consists of four variables. First, ApplicationTime, it corresponds to the time of the day a borrower started applying for a loan on Bondora’s website. It is split into four categorical variables: Night (midnight – 6:00 a.m.), Morning (6 a.m. – noon), Afternoon (noon – 6 p.m.) and Evening (6 p.m. – midnight)

Second, Weekday, listing the day of the week at which a borrower started applying for a loan on Bondora’s website (Monday, Tuesday, …, Sunday)

Third, Duration, that measures the duration in hours between the start of application and the final date and time when the loan is listed on the website.

Last, EarlyRepayment, that counts the number of early repayments in previous loans.

We created per model-version four different models:

(1) Distress = ApptimeCat + Weekday + EarlyRepayment + Duration

(2) Distress = Rating

(3) Distress = ApptimeCat + Weekday + Duration+ Rating

(4) Distress = ApptimeCat + Weekday + Early Repayment + Duration + Rating + Controls

7. Results

Table 2 in the appendix provides the descriptive statistics for the variables Gender, Country, and Education. Colum A show the statistics of the complete sample, section B show the statistic for the sample only using rating model 1 and section C show the statistics for the sample only using rating model 5. Table 3 in the appendix proved descriptive results of the variable age for the complete dataset as well as for the dataset with the borrowers that got rated by Bondora's rating model1. The average and distributions are very similar.

Figure 1 in the appendix shows the distribution of the given rating and the corresponding distress ratee in the complete dataset, AA being the best and HR being the worst. As expected, the distress rate increases the worse the rating gets.

Table 1 provides the regression results. Note, that we only used data of the rating model 1. Hence, our results are also based upon rating model version 1.

Important to note is that we use odds-ratio instead of coefficients to interpret our results. When the odds-ratio of a variable is less than 1, increasing values of the variable correspond to decreasing of the event's occurrence. When the odds-ratio of a variable is more than 1, increasing values of the variable correspond to increasing of the event's occurrence.

Table 1: Log-Regression Results

	(1) Rating Model 1		(2) Behavioural Footprint		(3) Rating Model 1 & Behavioural Footprint		(4) Rating Model 1, Behavioural Footprint, further controls	
Variables	Odd Ratio	p-value	Odd Ratio	p-value	Odd Ratio	p-value	Odd Ratio	p-value
Rating								
AA	0.335**	0.002			0.341**	0.002	0.354**	0.001
A	Basline	Basline			Baseline	Baseline	Baseline	Baseline
B	2.237**	0.000			2.223**	0.000	1.502**	0.005
C	2.571**	0.000			2.523**	0.000	1.765**	0.000
D	4.411**	0.000			4.317**	0.000	2.048**	0.000
E	6.585**	0.000			6.318**	0.000	2.206**	0.000
F	4.686**	0.000			4.507**	0.000	2.084**	0.000
HR	7.344**	0.000			6.968**	0.000	2.328**	0.000
Application Time								
Afternoon (noon- 6 p.m.)			Baseline	Baseline	Baseline	Baseline	Baseline	Baseline
Evening (6 p.m.- midnight)			1.068	0.181	1.018	0.727	0.955	0.392
Night (midnight- 6 a.m.)			1.531**	0.000	1.386*	0.000	1.179	0.065
Morning (6 a.m.- noon)			0.890*	0.007	0.931	0.113	0.944	0.229
Weekday								
Monday			1.012	0.796	0.996	0.951	1.021	0.767
Tuesday			1.201**	0.003	1.164*	0.020	1.171	0.222
Wednesday			0.950	0.425	0.936	0.339	0.974	0.713
Thursday			0.969	0.638	0.959	0.461	0.985	0.841
Friday			Baseline	Baseline	Baseline	Baseline	Baseline	Baseline
Saturday			1.006	0.940	0.991	0.925	1.032	0.743
Sunday			0.849	0.064	0.865	0.111	0.903	0.286
Duration			1.002**	0.000	1.001**	0.000	1.000	0.235
Early Repayment			1.09*	0.008	1.099**	0.005	1.123**	0.001
Constant	0.137**	0.000	0.516**	0.000	0.131**	0.000	0.178**	0.000
Control for Age, Gender, Education, Country	No		No		No		Yes	
Observations	12,922		12,922		12,922		12,922	
Pseudo R^2 (10x CV)	0.009		0.051		0.055		0.133	
AUC (10x CV)	0.642		0.556		0.652		0.739	

Note: The table provides the regression results of the four models we use to access the behavioural footprint. The odd ratios are taken from a log regression without 10-fold cross validation. The AUC results are based on 10-fold cross validation. Odd ratios equal to exp(coefficient). Pseudo R squared is equal to (1 - deviance/null deviance). ** p value below or equal to 0.005, * p value below or equal to 0.05.

The table provides results for four models. First the model only using the rating model, second the mode only using our behavioural variables (behavioural footprint), third the combined model of rating and footprint, and last we added controls to the combined model.

Model 1: Our AUC is 0,642 for model 1 (Rating only).

The Rating scores in model 1 represent the different levels of creditworthiness, where AA is best, and HR is worst. The odd ratios suggest what figure 1 in the appendix already suggested. The worse the score the higher the odds of distress. All coefficients are significant at the 0.5% level.

Model 2: Our AUC is 0,556 for model 2 (Behavioural Footprint).

Application Time:

When we take a look at the ApplicationTime and compare the highly significant odds-ratio of night (1,531) to morning (0,89), we can see that a loan applicant who is asking for a loan in the morning is 'sharper' in a sense that this moment in time decreases the individual's default risk, as compared to a loan applicant who is asking for a loan in the night and is less 'sharper' which increases the individual's default risk. This sharper can be explained through less impulsive behaviour or bearing less impact from sleep deprivation, or a combination of both. Both morning and night are significant at the 5% level.

Weekday

When checking the relevance of weekday on risk of default, we see no significant results, at least not at the 5% significance level. When we analyse at 10% significance, we see that an application on Sunday (p-value of 6%) can decrease the risk of default. Although we should be very careful with interpreting this weekday variable, because again it's not significant at the 5% level, the results are nevertheless interesting because it could be explained by our thesis and academic literature. Namely, that impulsive behaviour increases the risk of default, and that Sunday (rest day) is the day where people are the most relaxed, and thus less impulsive or bear less impact from sleep deprivation, which leads to a lower risk of default.

Duration

Duration is highly significant but doesn't have a great impact (Odds-ratio of 1,002) and is significant at the 0.5% level. Our results suggest that the higher the duration (time between an applicant creating an account and receiving the funding) the higher the risk of default. This result does not surprise, as it is exactly in line with our reasoning that an applicant whose duration is longer, probably will be less motivated or harder to identify (retrieve some information) and would either way increase the risk of default.

Early repayments

Early repayments have an odds ratio of 1,09, which is significant 5% level. This means that a loan applicant who is paying early increases its risk of default. This is an interesting result, as we didn't expect this. Our reasoning would be that, given that the loan applicant has enough financial power, the decision to pay early is a behavioural one and would decrease the risk of default. One could also argue that this result is not that strange, as from a theoretical perspective paying early is never to the benefit of the loan applicant. One could earn money by lending these early repayments, instead of using them to pay off their loans. Investing (and thus not paying earlier) would then lower the risk of default, which would be consistent with our results.

Model 3: Our AUC is 0,652 for model 3 (Rating + Behavioural Footprint)

The combined model of Rating and Behavioural Footprint has an AUC of 65,2%, one percentage point higher than the model only using Bondora's rating. Thus, adding the behavioural footprint increases discriminatory power. This is also shown in the ROC curve in figure 2 in the appendix. The gap between the 45% line and the curve corresponds to the AUC.

Model 4: Our AUC is 0,739 for model 4 (Model 3 + Controls).

Adding controls to the combined model increases the AUC by 11.3%. However, all behavioural variables expect Early Repayment become insignificant at the 5% level. This questions the true explanatory power of our variables.

8. Limitations

In our study, we find that these time variables have an effect, however, it is difficult to gauge the extent of the effect. There are certain limitations to our study.

First, while overall we see that there is an effect of behavioural variables, we are unable to measure individual effects for each of the variables i.e., duration, weekday, day, and time as well as early repayments. We can only state that collectively, they have an effect. For example, we have not accounted for the variables for the ones which had the application start date after it was listed as this was not coherent. Also, our behavioural proxies are only indicative of “habits” and whether they have explanatory power when predicting distress rates. Therefore, we cannot make final conclusions on the underlying economic mechanisms that cause the increase in discriminatory power of 1 percentage point.

Second, there were some inconsistencies in the data questioning the reliability of the dataset and of our analysis. For example, table 1 in the appendix shows that duration has negative values for model 2,3,4,5,6 and 99. Surprisingly, duration did not either have high odd ratios in our regression analysis (tables 1), although our intuition would assume some effect of duration of application. Other variables such as Default Date or Use of Loan had inconsistencies as well and were not used in our analysis for that reason

Last, we do not know how Bondora calculates its ratings, nor do we know how exactly Application Time is measured or tracked. Our results are limited to our assumptions how we interested the variables.

9. Conclusion

In this research, we have built a model to predict default risk. Instead of using traditional financial information, which is most of the time represented by a credit score (rating score on Bondora), we have also incorporated soft information to predict default risk. We searched for variables that we could identify as “habits’’ and could be captured by soft information collected by the online Bondora Loan Dataset, which could also have some predictive power for the risk of default.

So, when a borrower fails to make a timely payment (more than 60 days), Bondora has in its dataset a variable, which prescribes a label LATE to a loan. We use this variable as proxy for financial distress or risk of default. This is our independent variable. We have selected model version 1 as the rating model Bondora uses to ascribe a credit score to every loan application. We identified four relevant behavioural dependent variables: Time, Date, Duration and Early repayments. We have used the control variables: Gender, Age, Country, and Education. We have made four different models (1 through 4), where model 1 represents only the odd ratio of Bondora’s rating, model 2 represents only the odd ratio of our behavioural variables, model 3 combines Bondora’s rating and our behavioural variables, and model 4 adds control variable to model 3.

We have used these models to gain insight to how all these variables are related to default risk, and ultimately to answer our research question:

Do habits (information derived from soft information and behaviour treats) complement rather than substitute for credit score information to predict default risk?

Although, we did not improve the AUC of the basic model 1 (only Rating) by a lot when introducing our behaviour variables (model 3), increases the AUC by 1 percentage point (0,642 to 0,652), respectively. Also, when we consider how the odds ratio of our variables change when we combine the variables of rating and behaviour (model 3) and when we add control variables to it (model 4), we see that certain relationships between our behaviour variables and independent variable are indeed what we or academic literature would expect. For example, our reasoning for introducing the Application Time variable is that we would expect to see that a loan applicant who is asking for a loan in the morning is 'sharper' in a sense that this moment in time decreases the individual's risk of default, as compared to a loan applicant who is asking for a loan in the night and is less 'sharp' which increases the individual's risk of default. We see a significant effect for the night variable, both in the solo and combined model (model 2 & 3), which indeed has predictive power for the risk of default as we expected. Another example that is in line with our reasoning is the introduction of Duration. An applicant whose duration is longer, probably will be less motivated or harder to identify (retrieve some information) and would either way increase the risk of default. We found a significant effect for Duration, but this will disappear when introducing control variables. Therefore, we conclude that the answer to our research question is: Behavioural variables (habits) do complement rather than substitute credit scores for predicting default risk.

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10. Appendix

Tables

Table 1: Mean, Standard Deviation, Minimum and Maximum of the variable Duration for each Model Version of Bondoras rating model.

Model Version	Mean	Standard Dev	Min	Max
0	37.1	72.5	0	752.8
1	40.3	71.1	0	1968.3
2	28.7	40.2	-3	707.1
3	14.4	29.6	-3	211.4
4	10.1	27.8	-3	281.4
5	0.5	11.6	-3	216.5
6	-0.4	5.4	-3	169.7
99	-2.6	0.5	-3	-1.97

Note: This table provides the mean, standard deviation, min and maximum duration count for each rating model Bondora used over the years.

Table 2: Descriptive Statistics: Gender, Country and Education

A. All Borrowers				B.Borrowers of Model 1				C. Borrowers of Model 5			
Variable	Unit	N	Distribution	Variable	Unit	N	Distribution	Variable	Unit	N	Distribution
Gender		221,523	100%	**Gender**		12,922	100%	**Gender**		25,822	100%
0	Male	130,271	59%	0	Male	7,348	57%	0	Male	22414	87%
1	Female	78.593	35%	1	Female	5,432	42%	1	Female	2,433	9%
2	Undefined	12,659	6%	2	Undefined	142	1%	2	Undefined	975	4%
Country		221,523	100%	**Country**		12,922	100%	**Country**		25,822	100%
	EE	128,148	58%		EE	6,659	52%		EE	16,554	64%
	ES	26,774	12%		ES	3,339	26%		ES	4,367	17%
	FI	66,305	30%		FI	2,908	23%		FI	4,901	19%
	SK	296	0%		SK	16	0%		SK	0	0%
Education		221,523	100%	**Education**		12,922	100%	**Education**		25,822	100%
1	Primary	26,501	12%	1	Primary	151	1%	1	Primary	2,13	8%
2	Basic	6,126	3%	2	Basic	1,552	12%	2	Basic	903	3%
3	Vocational	57,892	26%	3	Vocational	2,856	22%	3	Vocational	4,616	18%
4	Secondary	76,91	35%	4	Secondary	4,911	38%	4	Secondary	10,616	41%
5	Higher	52,11	24%	5	Higher	3,462	27%	5	Higher	7,553	29%
-1	Undefined	1,984	1%	-1	Undefined	0	0%	-1	Undefined	4	0%

Table 3: Descriptive Statistics: Age

Variable	Unit	N	Mean	SD	P25	Median	P75
A. All Borrowers							
Age	Years	221,523	40.37	12.39	31.00	39.00	49.00
B.Borrowers of Model 1							
Age	Years	12,922	38.41	11.31	29	37	46

Table 4: Start and end date of Bondora's rating models.

Model Version	N	AppYear Min	App Year Max
0	4,569	2013	2014
1	12,922	2012	2015
2	7,946	2015	2016
3	1,039	2016	2016
4	7,861	2016	2017
5	25,822	2017	2018
6	159,387	2018	2022
99	1,977	2021	2022

Note: This table provides start date (min) and end date (max) of each rating model used by Bondora to access credit risk.

Table 5: Correlation Matrix

	AppTimeCat	Weekday	EarlyRepayment	Rating	Gender	Age_Q	Education	Country	Duration_Q
AppTimeCat	1	0.07022671	0.02702162	0.06648332	0.03605407	0.03200666	0.03473214	0.09148417	0.29412201
Weekday	0.07022671	1	0.02869902	0.02549122	0.02226278	0.02530155	0.02122589	0.03243839	0.19713019
EarlyRepayment	0.02702162	0.02869902	1	0.04833745	0.02396747	0.03186042	0.02878960	0.03017427	0.04771570
Rating	0.06648332	0.02549122	0.04833745	1	0.12553982	0.10878442	0.10637023	0.41669219	0.06948392
Gender	0.03605407	0.02226278	0.02396747	0.12553982	1	0.07518173	0.07535662	0.14640206	0.06612256
Age_Q	0.03200666	0.02530155	0.03186042	0.10878442	0.07518173	1	0.07902696	0.11818554	0.04032108
Education	0.03473214	0.02122589	0.02878960	0.10637023	0.07535662	0.07902696	1	0.20529684	0.04027832
Country	0.09148417	0.03243839	0.03017427	0.41669219	0.14640206	0.11818554	0.20529684	1	0.13408468
Duration_Q	0.29412201	0.19713019	0.04771570	0.06948392	0.06612256	0.04032108	0.04027832	0.13408468	1

Note: The table provides the correlation matrix using the Cramers V. Duration and Age were split into 10% percentiles and converted into categorical variables.

Figures

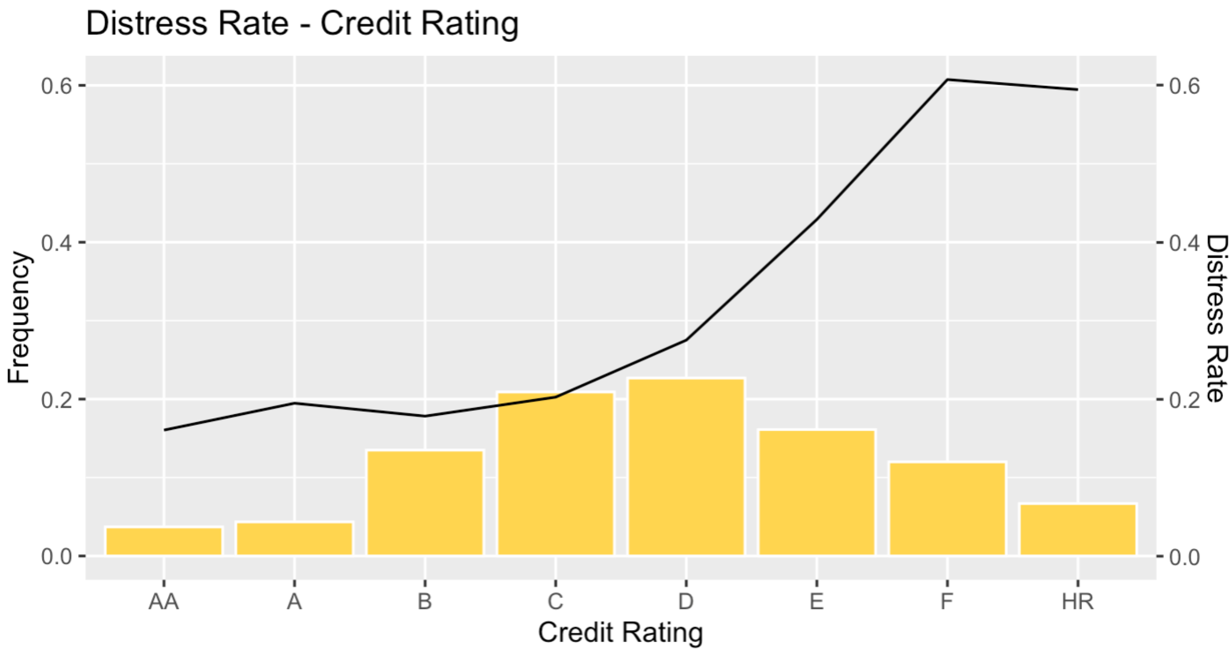

Figure 1: Distress Rates and Credit Ratings

Note: The left y axis corresponds to the frequency of each credit rating category. The right axis corresponds to the distress rate in each credit category

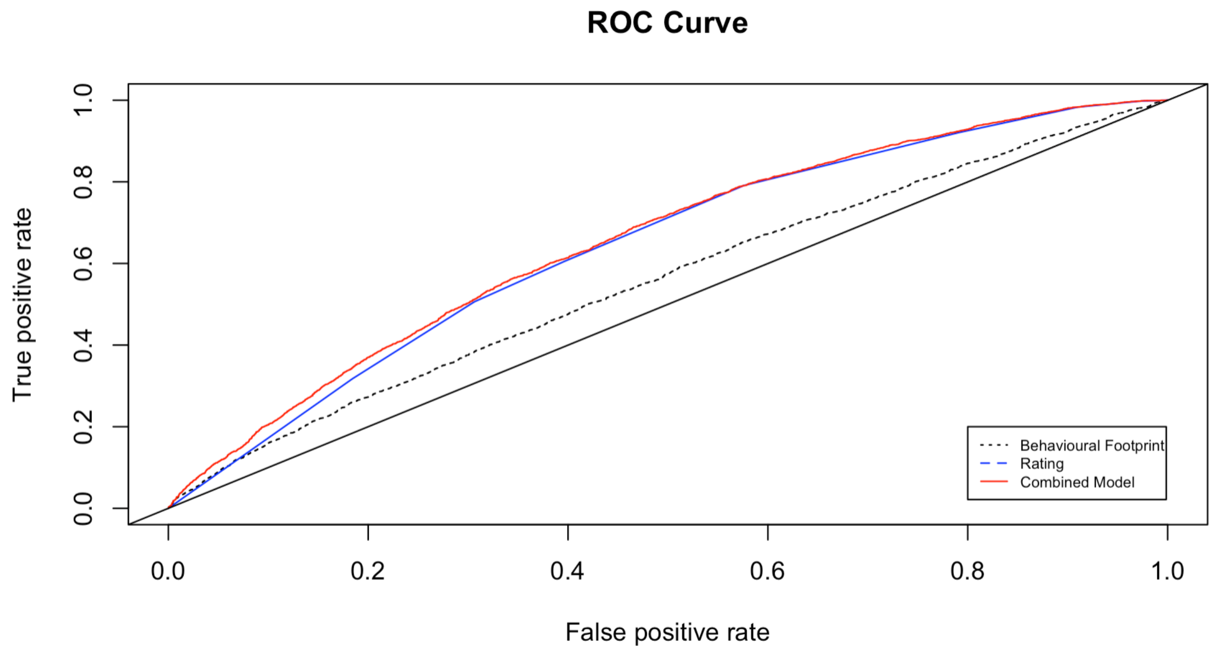

Figure 2: ROC Curves

Note: The graph shows the ROC curve of the three models. The 45% line equals an AUC of 50%. The area between the curves and the 45% line visualizes the AUC and therefore the predicable power of each model.