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Desilencing Complexities: The Financial Needs of Entrepreneurs on Welfare Benefits

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Access to financial resources for starting or developing an enterprise can be difficult, especially in the case of entrepreneurial groups who face limited options to participate in the economic mainstream. In addition, the recent COVID-19 pandemic has brought historically rooted inequalities to the forefront and exposed social vulnerabilities. Even though much has been done, especially in the social finance and microfinance space additional barriers to financial access exist. This paper focuses on entrepreneurs who depend on welfare benefits but seek financial access to either start or develop their enterprise in the Netherlands. Entrepreneurship may be one of the few key means for this particular group of people to gain independence from welfare benefits that are provided by government entities. In return, more entrepreneurial activity may reduce public expenditures. Latest national statistics show that COVID-19 reflected on the Dutch labour market with a 25% increase in the number of unemployment benefits between February and May 2020 (CBS, 2021). This study aims to capture possible intersecting forms of disadvantage by testing for interaction effects between the welfare benefit receiving entrepreneurs' age, gender, nationality and their creditworthiness. We draw on loan officer discretion literature to gain a better understanding of how the COVID-19 crisis in 2020 may have influenced the decision making behaviour of loan officers towards welfare benefit receiving entrepreneurs and potential intersecting forms of disadvantage. We analysed the dataset from a prominent microfinance institutions in the Netherlands who were impacted by the crisis as they had to move from on-sight personal visit to online interactions with prospective borrowers. The dataset comprises 42.763 loan applications between 2018 and 2020. We provide mixed evidence on how the pandemic may have affected loan officer behaviour and their ability to use discretion to grant and deny loans in comparison to previous years. We find that the likelihood of false positives may have increased in 2020 and recommend further research in this direction. Overall, the approach in this paper falls in line with the UN's agenda that emphasizes the need for more quantitative approaches focusing on intersecting social categories in order to gain a better understanding of inequalities.

Keywords: COVID-19, Loan Officer discretion, Microfinance, Quantitative intersectional approach.

1. Introduction

Inclusive entrepreneurship plays a vital role to ensure innovation and inclusive growth across the European Union. Still, some sections of the population remain less active in self-employment (OECD, 2019). In particular women, youth, seniors, immigrants and unemployed people are underrepresented in entrepreneruship activity as they encounter difficulties due to social personal conditions (Block and Wagner, 2010; Hart and Acs, 2011; Aliaga-Isla and Rialp, 2013; Maâlaoui et al., 2013). In the case of entrepreneurship out of unemployment, recent estimations by OECD (2019) show that the number of unemployed people returning to work as self-employed has declined across Europe since 2011.

Welfare benefit receiving entrepreneurs that receive support from the national government due to unemployment or due to the inability to work full-time for an employer are the main focus group of this study. In the Netherlands, the financial and social needs of entrepreneurs out of unemployment have been met by multiple government-led programmes (RVO, n.a.). Yet, gaps remain. As pointed out by the UN 2030 Agenda for Sustainable Development, quantitative approaches that test for possible intersecting forms of disadvantage are not well understood (UNDP, 2018). Financial policies that fail to consider aspects of multiple social categorizations may inhibit entrepreneurs to be fully recognized. In return, lenders may fail to meet the financial needs of marginalized entrepreneurs (Scott and Hussain, 2019).

Therefore, this study is motivated to better understand the effects of intersecting forms of disadvantage in which entrepreneurs out of unemployment may be situated. This approach may enable us to draw a wider picture of the lived experiences of entrepreneurs out of unemployment. Given the COVID-19 impact in 2020 this focus groups gains even more relevance. While the impact of COVID-19 was clearly visible amoung European countries, the Netherlands recorded one of the highest employment rates (EU-LFS, 2021). Nevertheless, the crisis still reflected on the Dutch labour market with a 25% increase in the number of unemployment benefits between February and May 2020 (CBS, 2021).

We apply a dataset that comprises 42.763 loan applications between 2018 and 2020 from the microfinance institution Qredits in the Netherlands. The institutions' target group includes welfare benefit receiving entrepreneurs. Qredits relationship based lending model is specifically designed to serve the financial needs of their target group who often miss the necessary company financials, personal collatoral and networks to attain commercial loans. This means that Qredits allocates resources through the collection of soft information. This is mainly done through face-to-face (non digital) meetings between the loan officer and the loan seeking entrepreneur. The COVID-19 crisis has had a great impact on the day-to-day lending procedures of loan officers at Qredits in particular because personal meetings with potential borrowers were impossible.

In order to quantitatively capture how the COVID-19 crisis may have influenced the decision making behaviour and lending outcomes towards welfare benefit receiving entrepreneurs and their potentially intersecting forms of disadvantage; we draw on loan officer discretion literature and manipulation in credit-scored lending (Puri, Rocholl, and Steffen, 2011; Brown et al., 2012; Berg, Puri,and Rocholl, 2013; Degryse et al., 2014; Mosk, 2014; Campbell, Loumioti, and Wittenberg-Moerman, 2019). Existing frameworks in discretion literature suggest that loan officers exert discretion based on soft information that cannot be readily captured by automated risk scoring models (Costello, Down and Mehta, 2020). While Qredits own credit risk score serves as a complementary tool within the loan officers lending decision-making process. Decision deviation from the risk score suggestion indicates that the loan officer draws on decisive factors other than those weighting in the score output. In other words, if loan officers use their discretion to influence the outcome of a lending decision, we expect deviations from the automated risk score recommendation to be larger for entrepreneurs out of unemployment. This is based on the assumption that disadvantaged entrepreneurs fail to provide the necessary input that would trigger a low risk score.

The role of human discretion and the value of the loan officer profession in assessing loan outcomes remains not well understood (Costello, Down and Mehta, 2020). To the best of our knowledge, we find no further quantitative research that attempts to identify the impact of distancing behaviour as a result of COVID-19 on relationship based lending practices. This in return, may have implications on loan officers ability to practice discretion in favour of disadvantaged entrepreneurs.

The remainder of the paper is structured as follows: The next section briefly touches upon related literature and the research hypothesis. Next, variables, data sources, methods and descriptive analysis are presented. In Section 4 we will present the results and Section 5 discusses and conclude.

2. The use of discretion in light of COVID-19 and intersecting forms of disadvantage

Traditional human loan assessment practices have shown not to be fully replacable, despite the evidence that automated risk scoring models increase operational efficiencies and decrease costs in microfinance. The use of loan officers discretion and personal judgement has been successful when financing opaque and risky borrowers, in particular through unprofitable episodes, like crisis (Chodorow-Reich, 2014; Chodorow-Reich et al., 2020). On the one hand, discretionary practices of loan officers rely on information, such as soft informatuon (Liberti et al., 2019) or gut instinct (Lipshitz and Shulimovitz, 2007) that may help to overcome information asymmetry problems which are prevalent in opaque borrowers. In return, the use of discretion may lead to more efficient resource allocation. On the other hand, some studies argue that advances in machine learning techniques and 'big data' have crowded out the necessity of human judgement. One strand of literature focuses on agency problems and cognitive biases playing a role leading to sub-optimal resource allocation (Hertzberg et al., 2010; Paravisini & Schoar, 2013; Campbell et al., 2019). While soft information may be important for small firms suffering from information asymmetry, evidence suggest that small firms chose to increase their distance because information technology can function as alternative personal visits (Petersen and Rajan, 2002). The research aligns with more recent studies who find a decreasing role for discretion over time, especially in the provision of small loans to opaque borrower due to information technologies (Cerqueiro et al., 2011).

Capturing the real value of loan officers discretion and production of soft information for opaque borrowers has proven to be difficult. Nevertheless, it has great implications on the loan performance and business models of modern microfinance institutions. Relevant information may be lost in score-based lending (Paravisni and Schoar, 2013) . This could occur because soft information is difficult to incorporate into statistical models or because other information is simply ignored if loan officers have no authority of integrating them in their decision (Rajan, Seru & Vig, 2015). In addition, because most machine learning and deep learning algorithms are based on black-box models, this could cause unfair treatment of customers. This practice raised a lot of concern and scrutiny from regulators. As pointed out by Paravisni and Schoar (2013) empricially evaluating the trade-offs in credit score adotption is ambigious given that each adoption is context specific and depends on organizational innovations compensation structures as well as changes in the environment (Paravisni and Schoar, 2013).

Hence, following the argumentation of Petersen and Rajan (2002), Paravisni and Schoar (2013) and Cerqueiro et al., (2011) the use of discretion and ability of soft information production in situations where relationship lending is no longer possible may reduce the ability of loan officers to make judgements based on information other than information provided through information technology. We test whether loan officers have, as a result of the COVID-19 distancing meaures relied relatively more on automated risk score models in 2020 compared to previous years. Smaller deviation from the automated risk model in 2020 compared to previous years would hint towards more reliance on hard information that is provided, which includes the risk score recommendation. Our hypothesis can be formulated as follows:

Hypotesis 1

The year 2020 is negatively associated with deviations from automated risk score recommendation compared to previous years.

While proactive policies to promote entrepreneurship of underrepresented groups such as young people have been implemented, participation rates for some of these populations have remained relatively low across Europe (OECD, 2019). For example, nearly half of the youth express an interest in entrepreneurship, while only 4.7% are reported to actively starting a business between 2014 and 2018. Moreover, entrepreneurs out of unemployment were found to be more likely to engage in entrepreneurial activity if they have been unemployed for only a short period of time (OECD, 2019). Emerging research on specific characteristics of entrepreneurs, such as by Scott and Hussain (2019) found that the reason for the low rate of entrepreneurship may be the diversity within one population. For instance, diversity among ethnic entrepreneurs may mask heterogeneity limiting the application of policy analysis for female ethnic minorities (Scott & Hussain, 2019). As a result, some segments of the population are difficult to account for due to the complexity of the interconnected nature of different social categorizations. Given the interconnectivity of global markets and freedom of movement across the European Union, accounting for the intersecting forms of advantages and disadvantage in entrepreneurship seems highly necessary.

Few studies have for instance focused on the impact of gender and ethnicity on financial access and entrepreneurial experience simultaneously. This is surprising given that women as well as ethnic minorities are similar because lower enterprise participation and performance are mainly caused by lower levels of resources (Scott & Hussain, 2019). In the same line of argumentation, business start ups of unemployed persons are generally smaller and require less capital than other start-ups. In addition, they have been found to be more active in industries with low market entry barriers and low capital requirements (Niefert and Tchouvakhina, 2006). Hinz and Jungbauer-Gans (1999) show that deficit in financial resources can be a great obstacle. Nevertheless, human capital is usually not the reason for deficits which may mean that unemployed founders come from a very specific subgroup of all unemployed persons. Amongst the broad strand of literature focusing on female financing, it has been shown that gender causes difficulties, especially in regards to the amounts of capital raised (Coleman & Kariv, 2014). While female entrepreneurs receive smaller loans than their male counterparts, research points towards the fact that there is no evidence of gender discrimination in access to finance (Bardasi, Sabarwal, and Terrell (2011). Nevertheless, women are more likely to found start-ups in sectors and sizes with low capital requirements (Carter and Shaw, 2006).

As argued by Costello, Down and Mehta (2020) if there is more discretion used by loan officers, one would expect the deviations from the credit score output to be larger for borrowers who may be considered disadvantaged. Given above information we propose to test for intersecting characteristics of age, gender and nationality. As we have no data indicating ethnicity, a nationality variable was used. Moreover, we test for significant associations of entrepreneurs out of unemployment in specific sectors as above literature hints towards disadvantaged groups being active in sectors with lower capital requirements. The interaction effect between welfare benefits and year of application is tested following argumentation above of Hypothesis 1. In addition, we test for quality of application in Hypotheses 4.

Hypotesis 2

Welfare benefit receiving applicants are positively associated with a lending outcome scenario in which the lending decision deviates from the recommendation of the automated risk score.

Hypotesis 3

The interaction effect between disadvantaged groups of applicants (x^1=young people or/and x^2=female or/and x^3=Non-Dutch nationalities) and welfare benefit receiving applicants is significant with the lending outcome scenario in which the lending decision deviates from the recommendation of the automated risk score.

Hypotesis 4

The interaction effect between (x^4=quality of application or/and X^5=year of application or/and X^6=business sector) and welfare benefit receiving applicants is significant with the lending outcome scenario in which the lending decision deviates from the recommendation of the automated risk score.

3. Data Source, Variables, Descriptive Statistics and Method

Data Source and Qredits decision-making process

The data is derived from the portfolio of Qredits, the only microfinance institution in the Netherlands. In fact, Qredits is a microfinance organisation established in 2009 to help promote start-ups and existing businesses of welfare receiving entrepreneurs in the Netherlands. The institution finances private micro-projects for people who would not normally qualify for a loan from conventional commercial banks. Thus, the creation of Qredits has greatly contributed to enhancing employment opportunities for multiple under-represented entrepreneurial groups in Netherlands. We use a dataset of client portfolios that comprises 42.763 applications between 2018 and 2020. The advantage of this study is that it covers the almost exhausitive supply of microredit in all parts of the Netherlands over a period of the last 3 years.
Qredits introduced its own machine-based risk score in 2017 to predict early signs of risk during the assessment of new applications. Due to the fact that of applicants are mainly start-ups opposed to existing businesses the model differs from traditional banking scoring models as business financials are less weighted. The machine-based risk score is useful in analysing collected data and increasing efficiencies of the decision-making process by combining over 1,200 data variables that may indicate potential risks. Scores range from -4 to 10 and are provided as complementary information source for the loan officer. Scores under 0 usually indicate missing information in the application. While applicants will never be rejected based on the initial risk score, a score between 0 and 7 may indicate a higher probability of loan risks. A benchmark of 7 or higher may trigger access to the Fast Track screening process. This means that no further client visits are necessary, despite a 30- minute call with the customer that in return, may speed up the screening process. Nevertheless, it is up to discretion of the loan officer to deviate from the initial recommendation and request a follow up meeting (Korynski and Stulen, 2019)

Variables

Our dependent variable is categorical in nature and captures four different scenarios depending on the extent of discretionary behaviour of the loan officers to deviate from the recommended machine-based risk score. Each scenario will be coded. Please find the matrix in Table 1. Table 2 summarises the dependent, independent variables as well as control variables.
We consider four possible scenarios:

1. **Benefit of the Doubt Scenario**: The credit risk score indicates higher probability of risk (Score between -4-6) but the Loan Officer grants partial or full amount of credit requested
2. **Downgrade Scenario**: The credit risk score indicates low probability of risk (Score between 7-10) but the Loan Officer denies credit request
3. **Fast-Track Scenario**: The credit indicated low risk (Score between 7-10) and the Loan Officer granted the credit
4. **High Risk Alignment Score**: The credit score indicated high probability of risk (Score between -4 -6) and the Loan Officer denied credit

Table 1

Lending Outcome Scenarios

	Low Risk Credit Score Output (Score between 7-10)	High Risk Credit Score Output (Score between -4 - 6)
Receives partial or full amount of requested credit	Fast Track Scenario (3)	Benefit of the Doubt Scenario (1)
Receives No Credit	Downgrade Scenario (2)	High Risk Alignment Scenario (4)

Independent Variables

The welfare benefit variable constitutes a binary variable that takes the value of 1 if the applicant recorded to be receiving welfare benefits at the time of application, and 0 if not. This includes WAO, WIA, WWB, WW, Wajong and Ziektewet. Almost ¾ of all welfare benefit receiving entrepreneurs receive WW or WWB which support people without income, employment anf fortune. Concerning our dataset, one can notice the prevelance of three ordinal variables: borrowers age, years of application and highest level of education. The year the application variable was coded into 3 values: 2018, coded as 1, 2019, coded as 2, 2020, coded as 3. Age of the applicant was recorded at the time of application. The age was then coded into 5 values: If the entrepreneurs was 25 and younger at the time application, coded as 1, If between 26-35, coded as 2, If between 36-45 coded as 3, If between 46-55 coded as 4, If 56 and older, coded as 5. Type of Business of the applicant seeking a loan was also recorded at time of application and coded into 4 values. We categorized the different buisness sectors in regards to their apparent similarities: Wholesale, retail, online retail and entertainment services, coded as 1; Construction, manufacturing and agriculture; coded as 2; Educational and financial services, information and communication, coded as 3; and Transport, health and maintenance services as 4. The Gender variable and Nationality status also constitute a binary variables which take the value of 1 if the applicant is female and Non-Dutch Nationality, perspectively, and 0 if Male and Dutch Nationality, perspectively. Perceived quality of application is a quality score given at the time of application and may reflect the perceived quality of the application and the information provided to the loan officer. The score is a continuous variable from 0 to 3. 0 represents the lowest quality and 3 the highest quality. Log has been taken for the variable in line with research by Lütkepohl and Xu (2010) who state that taking logs stabilizes variance.

Interaction Terms

We computed two interaction terms to test Hypothesis 3 and 4. These are the interactions between (1) Welfare Benefits and age (2) Welfare Benefit and gender (3) Welfare benefit and nationality (4) Welfare benefit and year of access (4) Welfare benefit and type of industry (5) Welfare benefit and quality of application. Including interaction terms may show multiplicative relationships and correlations between the above variables and thus demonstrate nuances of experiences of historically disadvantaged groups.

Control Variables

We controlled for the legal form of the business as this can also affect access to finance the entrepreneur. The variable is binary which takes the value of 1 if the applicant has a start-up or existing business without legal personality, and 0 with legal personality. We categorized existing legal structure in these two categories given that all business structures without legal personality will be personally liable for the debt of the start-up with private capital and belongs. If a start-up is set with legal personality the business owner will not be personally liable for the start-ups debt. Similarly binary variables were applied for variables income from entrepreneurial activity and income from existing salary which are indicators of financial stability of the entrepreneur. Moreover, martial status, highest level of education, product type and the requested loan amount were also considered.

Table 2

	Description	N	Mean	Median	SD	Min	Max	p25	p75
Dependent variables									
Loan decision scenario	Categorical variable: Value of 1 for Benefit of Doubt scenario; 2 for Downgrade Scenario; 3 for High Risk Alignment; 4 for Fast Track Scenario	42763	2.60	3.00	0.870	1	4	2.00	3.00
Independent Variables									
Microfinance applicant welfare benefit status H2									
Welfare benefits	Value of 1 when applicant receives welfare benefits at the time of application, 0 otherwise	42763	0.13	0.00	0.334	0	1	0.00	0.00
Relevant application details H3, H4									
Age	Ordinal Variable: 1 if ≤25; 2 if between 26-35; 3 if between 36-45; 4 if between 46-55; 5 if ≥56	42763	3.01	3.00	1.157	1	5	2.00	4.00
Nationality	Binary Variable: 1 if borrower identifies Non-Dutch, and 0 Dutch Nationality	42763	0.10	0.00	0.296	0	1	0.00	0.00
Gender	Binary Variable: 1 if borrower identifies as female and 0 otherwise	42763	0.28	0.00	0.449	0	1	0.00	1.00
Subjective quality of loan application	Continuous Score between 0 and 3 with 3 the highest possible quality score of application	42763	1.98	2.00	0.440	0	3	2.00	2.00
Business Sector	Categorical Variable 1 to 4 (refer to description for details)	42763	2.30	2.00	1.176	1	4	1.00	3.00
Year of Application H1									
Year of application	Categorical Variable: 1 if year 2018, 2 if year 2019; 3 if year 2020	42763	2.30	3.00	0.795	1	3	2.00	3.00
Control Variables									
Applicants personal financial and business information									
Income from entrepreneurial activity	Binary Variable: Value of 1 if entrepreneur has an active income generating business; 0 otherwise	42763	0.66	1.00	0.474	0	1	0.00	1.00
Income from existing salary	Binary Variable: Value of 1 if entrepreneur receives salary from an employer; 0 otherwise	42763	0.20	0.00	0.396	0	1	0.00	0.00
Business Structure	Binary Variable: Value of 1 if business structure is without legal personality, 0 if business structure is with legal personality	42763	0.80	1.00	0.401	0	1	1.00	1.00
Type of product	Categorical Variable: Value of 1 if Microcredit, 2 if Medium-sized credit; 3 if Microcredit in combination with flexible credit, 4 flexible credit	42763	1.73	1.00	1.071	1	4	1.00	2.00
Amount requested	Continuous variable: Loan amount requested at time of application by applicant	42763	37.613	25000	46.528	1500	500.000	10.000	46.000
Maritial status	Binary Variable: Value of 1 if entrepreneur is Single; Value of 0 if Married, Living together or in registered relationship	42763	0.42	0.00	0.493	0	1	0.00	1.00
Highest level of education	Ordinal variable: Value of 1 if Secondary education; 2 if Lower vocational education; 3 if Secondary vocational education; 4 if high vocational education and 5 if University education level	42763	3.31	3.00	0.963	1	5	3.00	4.00

Method

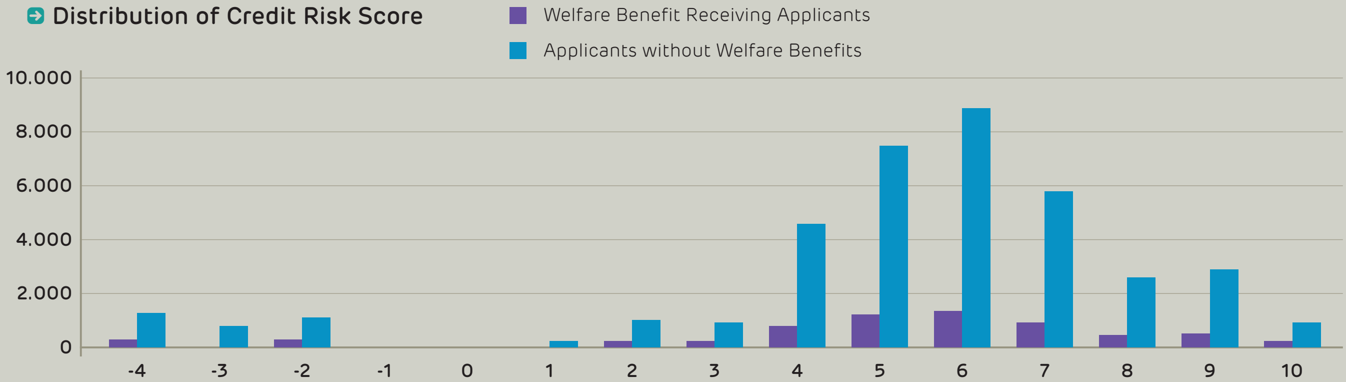
The outcome estimates were computed using multinomial logistic regressions in order to assess the influence of chosen independent variables on the four outcome scenarios. Chi-Square tests and binomial tests were done pre regression analysis due to the nominal and ordinal nature of the variables. We tested whether the proportions of applicants that fall into a category are signficantly different from expected proportions (Frankfort-Nachmias and Nachmias, 2008). Statistical data processing was performed with SPSS software. Moreover, the correlation values across explanatory variables are generally low and thus, do not threaten the stability of the estimation results.

Descriptive Analysis

A first look at the dataset shows that the percentage of loans being accepted was lower overall in 2020 compared to previous years, no matter the population group. This study, however aims to understand loan officer behaviour measured by deviation from the risk score recommendation. The data shows that lending decision deviation from the credit score recommendation occurs 36% out of all applications in the observed population (refer to Tabe 3 in Appendix 1). It indicates that about a third of all applications were either given the benefit of the doubt (risk score 6 or lower but loan was disbursed) or a "downgrade" (risk score 7 and higher but loan was not disbursed). As shown in Table 3 Appendix 1 16,1 % of all welfare receiving applicants fall under the benefit of the doubt scenario, opposed to 14,9% of applicants who do not receive welfare benefits. Welfare benefit receiving entrepreneurs were slightly more likely to fall under the benefit of the doubt scenario in 2019 and 2020 compared to their counterparts. In 2020, compared to previous years less applications fell under the Fast Track Scenario. Non- benefit receiving entrepreneurs were proportionally more likely to be "downgraded" between 2018 and 2020 compared to their counterparts.
As graphically depicted in Graph 1 the distribution of scores are highly similar between both population groups. The results suggest that both populations receive similar risk score recommendations on average. Hence, lending decisions that deviate from the recommendation of the risk score hint towards a situation in which loan officers use soft information or other critical available information to make a judgement. Between the years 2018 and 2020 the median score has not changed in both populations, being close to the score of 6. The graph shows that on average the score indicates a high risk score (Qredits defines them riskier if lower than 7). By definition, this leads to the conclusion that loan officers need to evaluate the majority of applications more closely.

Graph 1

Distribution of Credit Risk Score



In general, about every 7th applicant is welfare benefit receiving. There are some significant differences between both populations. Foremost, the average quality of loan application being significantly different at the 0.01 level with welfare benefit receiving applicants scoring slightly higher. This aligns with the results that welfare benefit receiving applicants are less likely to request medium sized credit products that are generally higher in amount of Euros.

4. Multinomial logistic analysis

The following tables report the results predicting the loan application outcome employing a three-step testing strategy: Model 1 analyses the main effect of our independent variables on the outcome scenarios. Model 2 accounts for the main effect welfare benefits on the likelihood of falling under the outcome scenarios. Finally, Model 3 analyses the interaction effect on the two scenarios (Please refer to tabel 4). This step also facilitated the estimation of the proportion of the variance explained by the addition of the interaction terms in our model after the controles and predictors had been accounted for.

Table 4

Model Fit Summary of the three step approach

	Model 1	Model 2	Model 3
Chi-Square	7094,65***	7195,641***	7251,235***
-2 Log Likelihood	81802,417	83473,471	83417,877
Goodness of Fit Deviance	1,00	1,00	1,00
Pseudo R2	0,174	0,176	0,177
Number of observations	42763	42763	42763

Benefit of the Doubt Scenario

In this scenario we analysed the significant relationships between chosen variables and the benefit of the doubt scenario compared to the high risk alignment scenario. We compare the odds ratios of an applicant receiving an automated high risk score but the loan officer grants the credit in comparison to not granting it. Identifying significant relationships mean that applicants with perspective characteristics are more likely to receive a credit because the loan officer deviates from the automated risk score.

Table 5

Model Fit Summary of the three step approach

	Model 1		Model 2		Model 3	
Variables	β	eβ (odds ratio)	β	eβ (odds ratio)	β	eβ (odds ratio)
Benefit of the Doubt Scenario (High Risk Score but receives credit)						
Intercept	-4,796***	NA	-4,822***	NA	-5,161***	NA
Age						
25 and younger	-0,455 ***	0,635	-0,454***	0,635	-0,522*	0,593
26-35	0,100	1,106	0,100	1,105	-0,030	0,970
36-45	0,197 ***	1,218	0,197***	1,218	0,179	1,196
46-55	0,206 ***	1,229	0,206***	1,229	0,007	1,007
Dutch Nationality	0,168 **	1,183	0,167**	1,182	0,166**	1,181
Gender (Male)	-0,245***	0,782	-0,245***	0,783	-0,047	1,182
Log_Perceived Quality	1,420 ***	4,137	1,421***	4,139	1,590***	4,906
Business Sector						
Wholesale, retail, online retail and entertainment services	0,010	1,010	0,010	1,010	0,208	1,231
Construction, manufacturing and agriculture	0,099	1,104	0,099*	1,104	0,412**	1,509
Educational and financial services, information and communication	-0,047	0,954	-0,047	0,954	0,319*	1,375
Business Structure with legal personality	-0,371 ***	0,690	-0,371***	0,690	-0,370***	0,691
Year of application						
Year 2018	0,696 ***	2,005	0,698***	2,009	0,588***	1,791
Year 2019	0,632 ***	1,881	0,633***	1,883	0,584***	1,801
Product Type						
Microcredit	-0,269***	0,764	-0,265***	0,767	-0,270***	0,763
Medium-sized credit	-0,224 **	0,800	-0,222**	0,801	-0,227**	0,797
Microcredit+ Flexible credit	-0,060	0,942	-0,061	0,941	-0,065	0,937
Log_Credit amount requested in €	-0,044 *	0,957	-0,044*	0,957	-0,044*	0,921
Highest Level of education						
Secondary Education	0,118	1,126	0,118	1,126	0,118	0,141
Lower vocational education	0,450 ***	1,568	0,450***	1,568	0,447***	1,564
Secondary vocational education	0,251***	1,286	0,252***	1,286	0,251***	1,284
High vocational education	0,176 **	1,193	0,176**	1,193	0,175**	1,191
Marital Status (Married)	0,207 ***	1,230	0,207***	1,230	0,207***	1,230
No Active Business	2,207 ***	9,092	2,207***	9,089	2,209***	9,104
No Income from paid salary	2,047 ***	7,747	2,047***	7,742	2,047***	7,747
Business Structure with legal personality	-0,371 ***	0,690	-0,371***	0,690	-0,370***	0,691
Applicant receiving no welfare benefits			0,034	1,035	0,426	1,531
Interaction Terms						
Applicant receiving no welfare benefits * Construction, manufacturing and agriculture					-0,362**	0,696
Applicant receiving no welfare benefit * Educational and financial services, information and communication					-0,426**	0,653
Applicant receiving no welfare benefit * Gender(Male)					-0,229*	0,796

Reference Category: Receives High Risk Score and No Credit Note: reference for gender is female, for age reference is 65 and older; for year of application is 2020; for eduction it is university level; for nationality is non-dutch nationality; for marital status it is single; for Industry Type (Transport, health and maintenance services), loan product type it is flexible credit. The results for Model 3 report only significant interaction terms among all 6 Interaction terms OR values greater than 1 signal positive association, while OR values smaller than 1 signal negative association
*p<.05; **p<.01; ***p<0.001

Downgrade Scenario

In this scenario we analysed the significant relationships between chosen variables and the downgrade scenario compared to the Fast Track Scenario. We compare the odds ratios of an applicant receiving an automated low risk score but the loan officer does not grant the credit in comparison to granting it. Identifying significant relationships mean that applicants with their perspective characteristics are more likely to not receive a credit because the loan officer identifies false positives.

Table 6

Multinomial Logistic Regression Results Downgrading Scenario

	Model 1		Model 2		Model 3	
Variables	β	e^{β} (odds ratio)	β	e^{β} (odds ratio)	β	e^{β} (odds ratio)
Downgrading Scenario (Low Risk Score but receives no credit)						
Intercept	3,668***	NA	3,450***	NA	3,052***	NA
Age						
25 and younger	0,620***	1,858	0,621***	1,861	0,801**	2,227
26-35	-0,083	0,920	-0,084	0,919	0,031	1,032
36-45	-0,167*	0,847	-0,165*	0,848	-0,082	0,921
46-55	-0,135*	0,874	-0,133	0,875	0,037	1,038
Dutch Nationality	-0,204**	0,815	-0,206**	0,814	0,145	1,156
Gender (Male)	0,204***	1.223	0,204***	1,226	0,360**	1,443
Log_Perceived Quality	-1,349***	0,260	-1,352***	0,259	-1,638***	0,194
Business Sector						
Wholesale, retail, online retail and entertainment services	0,123*	1,131	0,122*	1,130	0,247	1,280
Construction, manufacturing and agriculture	0,047	1,048	0,045	1,046	-0,139	0,870
Educational and financial services, information and communication	0,118*	1,125	1,117*	1,124	0,025	1,025
Year						
Year 2018	-0,267 ***	0,776	-0,257***	0,774	0,037	1,038
Year 2019	-0,036	0,065	-0,030	0,971	-0,027	0,974
Product Type						
Microcredit	0,300***	1,349	0,296***	1,344	0,297***	1,346
Medium-sized credit	0,410***	1,508	0,403***	1,496	0,403***	1,496
Microcredit + Flexible credit	0,155*	1,167	0,134	1,143	0,139	1,149
Log_Credit Amount requested in €	0,025	1,026	0,020	1,020	0,020	1,020
Highest level of education						
Secondary Education	-0,056	0,945	-0,058	0,944	-0,057	0,945
Lower vocational education	-0,017	0,983	-0,016	0,985	-0,015	0,985
Secondary vocational education	-0,109	0,897	-0,110	0,896	-0,109	0,897
High vocational education	-0,036	0,964	-0,036	0,965	-0,035	0,965
Marital Status (Married)	-0,160***	0,853	-0,159***	0,853	-0,159***	0,853
No active business	-2,135***	0,118	-2,137***	0,118	-2,136***	0,118
No Income from paid salary	-1,934***	0,145	-1,037***	0,144	-1,934***	0,145
Business Structure with legal personality	0,477***	1,611	0,479***	1,165	0,478***	1,613
Applicant receiving no welfare benefit			0,311***	1,365	0,757	2,132
Interaction terms						
Applicant receiving no welfare benefits * Year 2018					-0,332*	0,718

Reference Category Fast Track Scenario (Receives Low Risk Score and receives Credit) Note. No Credit Note: reference for gender is female, for age reference is 65 and older; for year of application is 2020; for eduction it is university level; for nationality is non-dutch nationality; for marital status it is single; for Industry Type (Transport, health and maintenance services), loan product type it is flexible credit. The results for Model 3 report only significant interaction terms among all 6 Interaction terms OR values greater than 1 signal positive association, while OR values smaller than 1 signal negative association
*p<.05; **p<.01; ***p<0.001

Results in Model 1 and Model 2 in both scenarios show similar significance and odd ratios, hence we will interprete results in Model 2 for both scenarios.
The odds of someone applying in 2018 and 2019 and being considered creditworthy despite an automated high risk score is 2 times greater in 2018 and 88,3% greater in 2019 than when applying in 2020. It proves that the automated credit score recommendation was more likely to align with the final loan officer decision in 2020 compared to previous years. However, in Table 6 we see that the likelihood of receiving no credit, despite a low risk score was also significantly higher in 2020. This means that the loan officers final decision deviated more in 2020 than in previous years, but in one direction only: Applicant receives a good score but receives no credit. Hence we reject Hypothesis 1. The results indicate that Loan Officers identified automated scores as false positives more so in 2020 than any previous years.
The positive coefficient for the welfare benefit dummy variable is not statistically signficant. Nevertheless, if we compare the results of tables 5 and 6 we find a significant relationship The odds ratio of the loan officer to make a decision that deviates from the automated score recommendation are 36% higher for non-welfare benefit receiving entrepreneurs compared to welfare benefit receiving ones. If deviations occur, however they are more likely to occur under the downgrade scenario and for applicants that do not receive welfare benefits. Moreover, the results do not present us with an indication on whether loan officers are more likely to deviate from the risk score recommendation for welfare benefit receiving clients. Nevertheless, we see that if welfare benefit receiving entrepreneurs apply and the automated score indicates low risk, the loan officer is more likely to align with the suggested risk recommendation and grants the loan in comparison to the case of non-welfare benefit entrepreneurs.
We reject Hypothesis 2 because we find no evidence that welfare benefit receiving applicants are positively associated with a lending outcome scenario in which the lending decision deviates from the recommendation of the automated risk score recommendation compared to their counterparts.
The interaction terms show that three out of six terms are significant. We accepted Hypothesis 3 and 4. There seems to be a significant relationship at the level <0.05 between the year of application and welfare benefits. Welfare benefit receiving clients are not as likely to be effected in 2020 than non welfare benefit entrepreneurs. This means that if welfare benefit receiving applicants apply and receive a good automated score, they are less likely to be downgraded by the discretion of the Loan Officer compared to non-welfare benefit receiving entreprenerus.
Welfare benefits alone do not have a main effect on the lending outcome, but the variables' significance is strengthened in relation to whether or not the welfare benefit receiving entrepreneur is female and on the type of industry. The probability of falling under benefit of the doubt scenario is higher being a female welfare benefit receiving entrepreneur compared to being male and not welfare benefit receiving. Compared to entrepreneurs who are not on welfare benefits it is more likely to fall under the benefit of the doubt scenario if the welfare benefit receiving entrepreneur works in the transport, health and mentainence services.
Beside the test of hypothesis we find the following results worth mentioning: The quality of the application is significant and positively correlated with the outcome scenario. Moreover, while it seems that being 65 or older increases the odds of falling under the benefit of the doubt scenario compared to young entrepreneurs, entrepreneurs between the ages 26 and 65 have the highest probability. In addition, if an applicant has no salary or no income from an active start-up or a business without legal personality, it does not reduce the probability of falling under the benefit of the doubt scenario. This means financial stability is not necessarily a factor that leads to the denial of the credit. Instead, this evidence suggests that there are other factors at play that led the loan officer to deviate from an initial high risk score but grant the credit nonetheless.

5. Discussion and Conclusion

We find mixed evidence about the way loan officer behaviour was impacted due to the COVID-19 restrictions in 2020. In 2020, loan officers were less likely to deviate from the risk score recommendation in comparison to previous years, despite the fact that the risk score output has on average not changed from previous years. This behaviour aligns with existing research that find a decreasing role of loan officers for discretion over time, especially in the provision of small loans to opaque borrower due to information technologies (Cerqueiro et al., 2011). Due to distancing regulations in 2020, loan officers were unable to visit clients in person. This practice used to be common at the microfinance institution under investigation. Missing types of soft information in the evaluation process might have led the officer to rely more on provided risk score output or other available information, such as quality of application. We were able to show a significant positive relationship between quality of application and lending outcome. Nevertheless, this study also finds that the likelihood of receiving no loan, despite a low risk score was also significantly higher in 2020. This means that the loan officers identifed more false positives than in previous years: Denying credit to customers that received a low risk score of 7 or higher. This may be explained by a diminished trust relationship between the entrepreneur and loan officer. Alternatively, the entrepreneur may have had not the opportunity to get across its motivations or entrepreneurial character, which may have caused the loan officer to deny the credit despite a good credit score output. We propose a more in-debt research to explore the reasons for the results.

We found no evidence that this behaviour may have led to disadvantages for welfare benefit receiving entrepreneurs. We found evidence of interaction effects on the lending outcome between gender and welfare benefit receiving applicants. In particular, female welfare benefit receiving entrepreneurs were more likely to receive a loan despite high-risk scores (score between -4 and 6) than male applicants that do not receive welfare benefits. Whilst this study was motivated to draw a wider picture of welfare benefit receiving applicants, we propose further investigation in other population groups to investigate multiplicative relationships between social categorizations. Further studies may help to demonstrate a more nuanced picture of the lived experiences of other underrepresented entrepreneurial groups.

This study contributes mainly to two areas of research. Whilst intersectional framing has become more popular in research as well as national policy making, quantitative approaches on intersecting social categories remain limited. Thus, in this paper we attempt to test a more complex nature of entrepreneurs accessing credit. Furthermore, we contribute to the literature of loan officer discretion and behavior and attempt to demonstrate its importance in serving the needs of disadvantaged entrepreneurial populations. The results of this study hint towards the possibility that if daily work tasks -such as soft information production- cannot be accomplished, lending outcomes may be impacted due to the pandemic in 2020 and 2021.

Appendix 1

Table 6

Multinomial Logistic Regression Results Downgrading Scenario

(Applicants with welfare benefits: N= 5470; Applicants without welfare benefits: N= 37293)

Dependent Variables

	Welfare benefits (%)	No Welfare benefits(%)
Loan Decision Scenarios**		
Benefit of the Doubt	16,1	14,9
Downgrade Scenario	15,9	21,6
Fast Track Scenario	11,0	10,7
High Risk Alignment	57,0	52,9

Independent Variables

	Welfare benefits (%)	No Welfare Benefits (%)
Receives Welfare benefits	12,79	87,20
Age		
25 and younger	8,0	8,2
26-35	28,9	30,1
36-45	28,2	27,1
46-55	22,8	22,3
56 and Older	12,1	12,3
Nationality		
Dutch Nationality	90,0	90,3
Non-Dutch Nationality	10,0	9,7
Gender*		
Male	73,1	71,7
Female	26,9	28,3
Average Subjective quality of loan application**	2,05	1,97
Business Sector		
Wholesale, retail, online retail and entertainment	35,7	36,4
Construction, maufactuing and agriculture	18,8	19,7
Educational and financial services, information and communication	22,1	21,8
Transport, health and maintenance wservices	23,3	22,2
Year of Application**		
2018	22,4	20,8
2019	30,2	27,1
2020	47,5	52,1

Control Variables

	Welfare Benefits (%)	No Welfare benefits (%)
Legal Entity		
with Legal Personality	21,0	20,0
without Personality	79,0	80,0
Product Type**		
Microcredit	68,5	62,5
Medium-sized credit	8,7	13,0
Microcredit+flexible credit	6,9	13,5
Flexible Credit	15,9	11
Income from entrepreneurial activity		
Yes	65,6	65,8
No	34,4	34,2
Income from existing Salary		
Yes	19,5	19,5
No	80,5	80,5
Educational Level		
Secondary education	7,3	7,7
Lower vocational education	4,2	3,8
Secondary vocational education	46,4	46,9
High vocational education	33,4	32,9
University education level	8,7	8,7
Average amount requested in EUR**	27397,19	39111,15
Maritual Status		
Single	41,0	41,8
Married, Living Together or Registered Partnership	59,0	58,2

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