

# Is the Lending Decision-Making Process **Affected by Behavioral Biases?**

-Evidence from Southern Italy

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Abstract

The objective of this article was to verify whether, in the decision-making process concerning bank loans issuance, managers have been influenced or not by how they perceive some personal characteristics of the applicant, even if these characteristics have nothing to do with the financial aspects typically analyzed to determine creditworthiness. In particular, we analyzed the impact of gender, age, beauty, race and education of the borrower on the probability to be funded. The study was conducted submitting face-to-face questionnaires to 212 officers working in the credit chain of 25 banks and data have been analyzed using the logistic regression model. The chosen setting was the south of Italy and in particular of the Campania region. The results show that there has been some influence of bias regarding gender, age and beauty, while no significant relationship has been found with reference to the racial discrimination or to the cultural level of the applicant. These results, which confirm the evidence already found in other settings by previous empirical analyses, would lead to highlight that there is an adverse selection mechanism in the provision of banks' credit capital.

## **Keywords**

Behavioral Biases, Banks, Non-Financial Firms, Decision-Making

# **1. Introduction**

Since the financial crisis began, in the third quarter of 2007, the weaknesses of the financial system in general and of the credit system in particular have been highlighted. For these reason, both researchers and policy makers have begun to ask themselves what the causes of the financial crisis were and how it could be

possible to prevent it to reoccur. The most important and pervasive conclusions reached by scholars and institutions have converged in highlighting that the credit system needed to be reformed once again, due to the lack of Basel II regulation to prevent the crisis in the financial industry. In this context, the bank regulation has been improved, introducing, through the Basel III accord, new and more rigorous capital and liquidity requirements in order to fulfill the need for stability of the bank industry and to enhance savers trust in the financial system. The main hypothesis underlying this new regulatory effort is that banks adverse selection in the lending process has been due to the inability to estimate creditworthiness of their clients and that this led banks to suffer a great amount of non performing loans and, as an unavoidable outcome, a lack of capital and liquidity. As a theoretical consequence, no space has been given by researchers and policy maker to the behavioral approach to credit issuance. We believe that the credit misallocation and, consequently, the bank crisis can be partially explained by behavioral biases in which banks officers may have incurred during their decision making process. This different perspective gives momentum to a new approach of assessing the bank crisis. It seems that a behavioral analysis regarding the lending process may be needed to determine if banks could have rejected valuable investing opportunities because of their officers biased mental process. Similarly, some poor project may have been financed because of the same bias or the demand of loans may have been affected by the perception of the officers' biases, which could have discouraged valuable firms even to apply for a loan. Moreover, once we have recognized that in a way the credit misallocation could be explained by behavioral biases, we could question the effectiveness of the regulatory policy, which, according to some evidence given by the scholar in the field, is leading to a significant credit crunch. Therefore, the purpose of this paper is to establish whether, and to what extent, the decision-making process regarding loan issuances by banks could have been affected by behavioral biases. The main contribution of this paper to the existing literature can also be found in the specific setting we've chosen. Indeed, in recent years, the focus on the Italian credit market has been certainly important, mostly because the majority of banks had suffered a great amount of non performing loans. This new concerns are shaping a significant decreasing in the credit issuance; both because of supply and demand side reasons. According to the Bank of International Settlement, since 2011, the amount of bank credit to non-financial firms, in percentage of the GDP, decreased from 92.5% to 83.5% in 2016 (BIS statistical tools, data available on the BIS website, Table F 2.4, 2016). Therefore, assessing if behavioral biases have had an effect on the loan issuance decision, in this context, can even be more interesting. The paper is organized as follows. In the second section we've reported the literature review concerning the main behavioral biases and their relation with the credit issuance. In section three we described the data gathering and methods. The fourth section is dedicated to the analysis of the results of the empirical analysis and in the last section we've concluded summing up the main contribution of the paper, its limitations and some hypotheses of future research directions.

#### 2. Literature Review

Studies concerning the behavioral finance date back to the late 1970s, but it is only in relatively recent years that this field has gain significant attention in the academic literature. The behavioral approach intends to demonstrate that the forms of rationality that shape individual behavior are frequently far more complex than how is typically assumed in the traditional economic studies, which tries to understand financial dynamics through models that assume individual rationality [1]. It results in a different perspective, strongly based on sociology and psychology, designed to take in to consideration the biases that may determine choices different from the ones suggested by the traditional economy. As a consequence, this new scientific research area has the objective to create a link between classical finance and individual behavior [2]. This new research field has been defined in different ways. Shefrin [3], for example, has defined the behavioral approach to finance as the application of psychology research findings to the analysis of people behavior in decisions concerning financial issues. Shleifer [4] argues that it explains human failure in competitive markets. According to Lintner [5], behavioral finance gives a description of the way people read and use information when making investment decisions. Though different, all these definitions can lead us to define the behavioral finance as a scientific discipline which, relying human psychological and sociological insights, have the fundamental aim of providing a realistic explanation of decision making in the financial context. Scholars in the field of behavioral finance have highlighted that when it comes to analyze the decision-making process, people tend to incur in some mental shortcuts, leaded by internal and external dynamics, which may drive their final financial decision. These errors may occur both when information are collected or processed. Typically, cognitive biases occur when collecting information and other biases, such as emotional or social biases, occur when processing information. However, when it comes to behavioral biases classification, scholars in the field of behavioral finance and in the field of psychology have proposed different possibilities. According to Peòn, Antelo and Calvo-Silvosan [6], researcher in the field used different classification rules and different names for concepts that are mostly similar. The classification given by Kahneman, Slovic and Tversky [7] is composed by seven categories (representativeness, causality and attribution, covariation and control, overconfidence, conservatism, availability, and judgmental biases in risk perception), the one given by Tversky and Kahneman [8] falls into five categories (framing effects, nonlinear preferences, source dependence, risk seeking and loss aversion), another classification, such as the one given by Plous [9], falls into the following categories: perception, memory and context can be classified in a subgroup, heuristics and biases in another subgroup, framing in a third separated group and models of decision-making and social effects in the last two groups. Shiller [10] included in

his classification the prospect theory, regret and cognitive dissonance, mental accounting, representativeness and overconfidence. Akerlof and Shiller [11] enounced five aspects of animal spirits, including feedback mechanisms, attitudes about fairness and social contagion. Therefore is extremely difficult to find a common used classification. However, what really matters is not the classification, but the effects produced by psychological and sociological biases on the decision-making procedure and result. The field of behavioral finance is mostly dedicated to capital markets in the attempt to explain why there is a mispricing in the stock market, which means that the value of a stock doesn't reflect its fundamentals. There is a huge body of literature trying to explain the failure of the well-known efficient market hypothesis. Barberis and Thaler [12], as well as and Kaniel et al. [13], argue that significant deviation of prices from their fundamental values are due to traders irrational behavior and that this irrational behavior is due to psychological biases. Empirically, scholars found a significant relation between the irrational behavior and some biases such as overconfidence, mental accounting, regret and loss aversion, herding, overreaction or familiarity [14]. When it comes to the credit market, literature is not anymore that extensive. However some typical biases concerning prejudice in loan issuance have been analyzed. Female discrimination, for example, is a topic that has been pretty much addressed [15] [16] [17] as well as race, age or education [18] [19] [20]. A summary of the main empirical evidence concerning the biases used in our study is presented below.

Gender: The literature in the field of behavioral finance has always had the theme of gender discrimination at the center of attention. Therefore, the possibility that women are discriminated in the provision of credit has been analyzed several times both from a theoretical point of view and empirically. Ongena and Popov [21], analyzing differential in credit access in a sample of over five thousands firms in seventeen countries, found that, controlling for sales growth and other financial information, the credit access is more challenging for female owned firms rather than for male owned ones, in countries affected by an higher gender bias. The phenomenon is also explained by the fact that, in these countries, female applicants believe their demand for credit will be denied. In the same way Moro et al. [22] argue that firms can be financially constrained also because female applicants anticipate the rejection and therefore are less likely to apply for a loan. Buttner and Rosen [23], as well as Stevenson [24], argue that, among other stereotypes, bank officers believe that characteristics of successful entrepreneurs may be more often found in male entrepreneurs. Orhan [25] found that credit access is far more challenging for woman because they do not fit the stereotype of the entrepreneur profile when it comes to some attributes such as self-confidence. The same findings have also been shown by Herz [15] and Muravyev et al. [26], providing evidence that banks discriminate against woman applicants.

Age: The age of the applicant is another commonly studied factor in the field

of behavioral biases affecting credit issuance. Empirical evidence, concerning how the age of the applicant may influence the decision-making process of a bank officer, is though ambiguous. In some studies such as the ones conducted by Nguyen and Luu [27], Slavec and Prodan [28] and Fatoki and Odeyemi [29] no evidence of age bias has been provided. However, Nguyen and Luu [27] and Abdulsaleh and Worthington [30], among others, found that age does have an effect on the capability to succeed in loan issuance.

Race: Racial discrimination in the field of credit allocation has been analyzed several times in recent years. In a paper written by Bayer, Ferreira and Ross [31], controlling for credit score and other risk factors, has been found that actually there is a cognitive bias concerning ethnic differences when it comes to bank officers valuation of their applicants. The authors investigated this topic in seven metropolitan areas from 2004 and 2007 and provide evidence that African and Hispanic borrowers are 103 and 78% more likely to receive higher cost of mortgages. Blanch flower *et al.* [32], using data from 1993 and 1998 national surveys of small business finances, conducted an analysis on small business and found that black-owned firms were twice as likely to be denied credit, even after controlling for creditworthiness. Likewise, in a study conducted by Storey [33] in the market for loans from banks to SMEs in Trinidad and Tobago, the result was a clear racial disparity in the decision concerning loan issuance. African applicants, controlling for other factors, reported higher denial rates compared to other ethnic groups.

Education: There is a wide literature assessing how the level of education can affect the way banks perceive the applicant. Generally speaking, banks believe that higher educated applicant are more creditworthy than less educated owners/managers and this can lead to an lower probability to get rejected when applying for a loan. According to this theoreticalhypothesis, several studies investigated the relation between education and access to credit. Zarook *et al.* [34] as well as Slavec and Prodan [29] found evidence of a positive correlation between the age of the applicant and the access to credit. Same findings have been found, among others, by Pandula [35], Kira [36], Mukiri [37], through entrepreneurial orientation, and Le *et al.* [38], through networking capabilities [18]. Therefore there is a certain convergence in believing that education has a positive effect of banks officers when deciding whether reject or approve a loan application.

Beauty: Beautiful people, according to some previous study such as Andreoni and Petrie [39], Olivola and Totorov [40] are perceived to be more productive and more confident. Same findings are shown in a paper written by Ravina [20] where the author investigates borrower characteristics in the United States. The findings suggest that ugly applicants suffer discrimination when it comes to assess their creditworthiness and that they are not more likely to incur in a non-performing debt service behavior.

#### 3. Data Gathering and Methodology

In order to investigate whether mental processes affect decision making in the

bank industry and, more specifically, in the loan issuance process, we implemented structured questionnaire. The target sample of the Italian banks consists of managers and staff members of credit institutions operating in Italy. Specifically, officers assigned to the various phases of the credit initiation and authorization process. The structured questionnaire was submitted to 212 managers and officers working in the following 12 banks: Artigiancassa, Banca Apulia, Banca del Sud, BCC, Banca di credito cooperative dell'Alto Casertano e Basso Frusinate, Banca di Sconto e Conti Correnti, Banca di Verona, Banca Fideuram, MPS, BNL, Banca Popolare del Mediterraneo, Banca Popolare dell'Emilia Romagna, Banca Popolare di Ancona, Banca Popolare di Puglia e Basilicata, Banca Popolare Etica, Banca Promos, Banca Sella, Cariparma, Credem, Deutsche Bank, Intesa Sanpaolo, MPS Capital Service, Unipol, Unicredit and Widiba. The questionnaire has been submitted through face-to-face interviews. The overall data gathering process last 3 months, from May to July 2017, which included the time needed for the preparation of the survey, for submission and, finally, for the analyzing data. Some extra time was dedicated to the pre-testing, to assess the cogency of the questionnaire design and fill some gaps. In order to measure the most important dimensions that capture behavioral biases, we've investigated the following variables, which are consistent with the ones investigated by a wide body of literature. As a dependent variable we used the probability of getting the application accepted by the bank officer. As independent variables we used personal biases such as: age, gender, race, education and beauty. In order to control for traditional economic valuation, we included in the questionnaire some typical variables used to measure clients creditworthiness both at firm level and at a higher level of analysis. Macroeconomic and industry information and trends as well as firm's financial fundamentals (balance sheets, leverage ratios, rating, guarantees) were investigated and generated one independent control variable. We used the Logistic Regression Model to determine if the probability to get a loan changes depending on applicant's personal characteristics. This model is particularly useful when the dependent variable is dichotomous and is exemplified by the following equation. This model has been used in previous similar researches in the field such as in Ogubazghi and Muturi [18].

$$P(Y) = \frac{1}{1 + \exp^{-\left[\alpha + \sum_{i=1}^{k} \beta_i(X_i) + \varepsilon_i\right]}}$$

According to this model, P(Y) represent the probability of the firm to get the loan.  $\beta_i$  are the regression coefficient for each variable.  $X_i$  are the independent variables ( $X_1$  = Gender,  $X_2$  = Age,  $X_3$  = Race,  $X_4$  = Education,  $X_5$  = Beauty;  $X_6$  = financial information).  $\varepsilon$  is the error term and  $\alpha$  is the Y intercept. To analyze data we used SPSS 17.

### 4. Results and Discussion

In this section we are showing the result of the logistic regression, specifically the

binary logistic regression, we performed. We had 212 cases involved in our analysis and six explanatory variables, the ones described in the previous section, and we used them to predict our binary outcome that was being accepted or rejected when applying for a loan. First of all we ran a correlation analysis (**Table 1**), as a preliminary step, between our predicting and outcome variables, to see if there was some kind of relationship and to have some idea of what to expect from our predicting model.

The correlation table shows that loan application acceptance is positively correlated, in a significant way, with gender, age and beauty. This means that the higher is the age, the higher is the probability of being accepted and that similar

	Correlation table							
		Credit	Gender	Age	Race	Education	Beauty	Financial
	Pearson correlation	1	0.186**	0.165*	-0.060	0.023	0.207**	-0.093
Credit	Sig. (2-tailed)		0.007	0.016	0.388	0.739	0.002	0.176
	Ν	212	212	212	212	212	212	212
	Pearson correlation	0.186**	1	0.666**	0.518**	0.344**	0.313**	-0.020
Gender	Sig. (2-tailed)	0.007		0.000	0.000	0.000	0.000	0.768
	Ν	212	212	212	212	212	212	212
	Pearson correlation	0.165*	0.666**	1	0.452**	0.386**	0.527**	-0.070
Age	Sig. (2-tailed)	0.016	0.000		0.000	0.000	0.000	0.310
	Ν	212	212	212	212	212	212	212
	Pearson correlation	-0.060	0.518**	0.452**	1	0.652**	0.076	0.158*
Race	Sig. (2-tailed)	0.388	0.000	0.000		0.000	0.271	0.021
	Ν	212	212	212	212	212	212	212
	Pearson correlation	0.023	0.344**	0.386**	0.652**	1	0.028	0.242**
Education	Sig. (2-tailed)	0.739	0.000	0.000	0.000		0.682	0.000
	Ν	212	212	212	212	212	212	212
	Pearson correlation	0.207**	0.313**	0.527**	0.076	0.028	1	-0.431**
Beauty	Sig. (2-tailed)	0.002	0.000	0.000	0.271	0.682		0.000
	Ν	212	212	212	212	212	212	212
	Pearson correlation	-0.093	-0.020	-0.070	0.158*	0.242**	-0.431**	1
Financial	Sig. (2-tailed)	0.176	0.768	0.310	0.021	0.000	0.000	
	Ν	212	212	212	212	212	212	212

Table 1. Correlationtable.

\*\*. Correlation is significant at the 0.01 level (2-tailed). \*. Correlation is significant at the 0.05 level (2-tailed). Source: author's calculation on data collected on data collected with face-to-face interviews and question-naire.

result can be found when it comes to gender and beauty. Males and beautiful applicant are positively correlated with the probability of being accepted. There fore we expected these three variables to be good predictor for loan acceptance. On the other way race, education and financial aspects were insignificantly correlated with the dependent variable. After running the correlation analysis, we tested the null hypothesis which shows a correct overall predicting ability in credit rejection around 64%, so the model would predict credit acceptance or rejection, without any predicting variable involved in the model, about 64% of times. What we expected was that our predicting model would be able to predict a higher percentage of correct prediction compared to the null hypothesis. The next table (**Table 2**) shows how strongly variables would be able, individually, to create a significant model. As you can see three (gender, age and beauty), out of six variables, have a p-value less than 0.05. This means that, individually, gender, age and beauty have a good predictability for credit issuance, which is consistent with the results of the correlation table.

The next table (**Table 3**) shows the omnibus test of model coefficients. It looks at the model compared to the null hypothesis that we had. The significant level is less than 0.05 (it was 0.002 displaying a chi-square of 20,310) that means that our variables combined in a model will succeed in predicting credit issuance.

The model summary, reported below in **Table 4**, explains of much of the variance of the dependent variable can be explained by the model. As you can see

	Variables not in	Variables not in the Equation				
	Score	df	Sig.			
Gender	7.308	1	0.007			
Age	5.752	1	0.016			
Race	0.754	1	0.385			
Education	0.112	1	0.737			
Beauty	9.096	1	0.003			
Financial	1.842	1	0.175			
	19.930	6	0.003			

Table 2. Variables not in the Equation.

Source: author's calculation on data collected on data collected with face-to-face interviews and questionnaire.

#### Table 3. Omnibus test of model coefficients.

Omnibus test of Model Coefficients							
	Chi-square df Sig.						
Step 1	Step	20.310	6	0.002			
	Block	20.310	6	0.002			
	Model	20.310	6	0.002			

Source: author's calculation on data collected on data collected with face-to-face interviews and questionnaire.

Table 4.	Model	summary
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Model Summary								
Step	-2 log likehood	Cox & Snell R-Square	Nagelkerke R-Square					
1	255,185ª	0.091	0.126					

Source: author's calculation on data collected on data collected with face-to-face interviews and questionnaire.

the model is able to explain approximately the 13% of the variance in the dependent variable. This is a decent result, but definitely not very high.

In the next table (**Table 5**) we show the result of the Hosmer-Lemoshow Test and the contingency table. In this test, if the p-value is greater than 0.05, it means that we have a good predicting model. The test actually performed in a good way, reporting a p-value of 0.546 with a chi-square of 6912.

The contingency table for the Homer and Lemeshow Test progressively tries to fit the model to the actual predicted outcomes. The observed number of accepted loans was 21 and our model predicted 20.1. Of course the closer this two number are together, the better the model is and therefore we can say we designed a good model according to this analysis. The classification table (**Table 6**) shows how good our model was in predicting the outcomes compared to the null hypothesis. It shows that our model can predict a higher percentage (68%) compared to the null hypothesis, which would predict the 64%. So we can say the model is doing well in the predictability.

The last table (**Table 7**) is showing for each variable the beta coefficient that can be used to create our regression equation. Moreover, having a look to the odd ratios, we can see which variable can give higher probability of being accepted or rejected when applying for a loan. In other words, the higher is this coefficient related to each variable, the more likely will be the acceptance of a loan application. It gives an idea of the magnitude of the effect that each of the variables might have on the predicted outcome. For example, the model clarifies that males have 1.2 times the probability of being accepted when applying for a loan.

The result of the statistical analyses displayed in this section of the paper show that there is actually some influence of behavioral biases affecting mental processes of bank officers when they have to decide whether to accept or reject a loan application. Particularly, we found that the probability of being accepted when applying for a loan is higher when the applicant is a man and when the applicant is older and is good looking. No evidence of any influence given by race or education on the probability of being accepted or rejected has been found. This evidence is consistent with several studies in the field assessing the relation between credit allocation and behavioral biases. However, unlike our findings, a wide range of literature had also found that race discrimination, as well as the level of education, is somehow present when investigating prejudice in credit allocation. 
 Table 5. Hosmer-Lomeshow test.

Hosmer-Lemeshow Test							
Step	Chi-square	df	Sig.				
1	6.912	8	0.546				

	Contingency Table for Hosmer-Lemeshow Test								
		Rej	Reject Accept						
		Observed	Expected	Observed	Expected	Total			
	1	11	13.660	10	7.340	21			
	2	13	11.038	8	9.962	21			
	3	10	9.399	11	11.601	21			
	4	7	8.256	14	12.744	21			
Store 1	5	7	7.453	14	13.547	21			
Step 1	6	10	6.537	11	14.463	21			
	7	6	5.723	15	15.277	21			
	8	3	5.042	18	15.958	21			
	9	5	4.052	15	15.948	20			
	10	3	3.839	21	20.161	24			

Source: author's calculation on data collected on data collected with face-to-face interviews and questionnaire.

#### Table 6. Classification table.

Classification Table								
			Predicted					
Observed			Cr	Percentage				
			Reject	Accept	Correct			
	Credit	Reject	23	52	30.7			
Step 1	Credit	Accept	16	121	88.3			
	Overall percentage				67.9			

Source: author's calculation on data collected on data collected with face-to-face interviews and questionnaire.

## **5.** Conclusion

The objective of this article was to investigate the existence of social biases that can influence the perception of bank officers in granting a loan, thus demonstrating that the financial crisis that has hit the bank industry can be partially explained by a mechanism of adverse selection that occurs as a result of biases that may have limited the selection of profitable investments in non-financial firms. The article fills a gap in the literature especially with reference to the chosen geo-economic setting, since the analysis has no precedents in southern Italy.

	Variables in the equation								
		D	C F	147 11	10	0.	F (D)	95% CI for EXP(B	
		В	5.E.	vv ald	dī	51g.	Exp(B)	Lower	Upper
Step 1(a)	Gender	0.191	0.081	5.514	1	0.019	1.211	1.032	1.421
	Age	0.021	0.107	0.039	1	0.843	1.021	0.829	1.258
	Race	-0.286	0.108	6.974	1	0.008	0.751	0.608	0.929
	Educa- tion	0.121	0.104	1.355	1	0.244	1.128	0.921	1.382
	Beauty	0.168	0.109	2.348	1	0.125	1.182	0.954	1.465
	Financial	-0.025	0.140	0.031	1	0.860	0.976	0.741	1.284
	Constant	-0.056	1.084	0.003	1	0.959	0.945		

Table 7. Variables in the equation.

a. Variables entered on step 1: Gender, Age, Race, Education, Beauty, Financial. Source: author's calculation on data collected on data collected with face-to-face interviews and questionnaire.

From the results that were found, we could verify the existence of some effect of social bias on the provision of credit. In more detail, the article highlights how women are discriminated against men in officers' choice regarding the acceptance of a credit application; moreover, in this territory, it seems that bank officers still have greater confidence in older borrowers. Finally, a positive effect on the perception by the banks regarding the beauty of the borrower was found. No evidence has been found concerning discrimination regarding race and cultural level of those applying for credit. This study has potential implications for both companies and policy makers. With reference to the first ones, we highlight which characteristics seems to be more appreciated by bank officers and this may lead firms to select the appropriate applicant in order to raise their possibility to be positively valuated. On the other hand, policy maker may have a more challenging problem to analyze when orienting their policy in order to protect banks from non-performing loans. Behavioral biases seems to have some influence on the credit decision making process, that means that provision concerning the creditworthiness, such as the ones put in place with the Basel accords, may only partially solve the problem. More in depth analysis concerning how to mitigate the effects of these social biases should be put in place.

#### References

- [1] Legrenzi, P. (2005) Creatività e Innovazione. Il Mulino, 1-129.
- Guiso, L., Sapienza, P. and Zingales, L. (2004) The Role of Social Capital in Financial Development. *American Economic Review*, 94, 526-556. https://doi.org/10.1257/0002828041464498
- Shefrin, H. and Statman, M. (2000) Behavioral Portfolio Theory. *Journal of Finan*cial and Quantitative Analysis, 127-151. <u>https://doi.org/10.2307/2676187</u>
- Shleifer, A. (2000) Inefficient Markets: An Introduction to Behavioral Finance. Oxford University Press, 1-216. <u>https://doi.org/10.1093/0198292279.001.0001</u>
- [5] Lintner, G. (1998) Behavioral Finance: Why Investors Make Bad Decisions. The

Planner, 1-8.

- [6] Peón, D., Antelo, M. and Calvo, A. (2016) Overconfidence and Risk Seeking in Credit Markets: An Experimental Game. *Review of Managerial Science*, 10, 511-552. <u>https://doi.org/10.1007/s11846-015-0166-8</u>
- Kahneman, D., Slovic, P. and Tversky, A. (1982) Judgment under Uncertainty: Heuristics and Biases. Cambridge University Press, 1-557. https://doi.org/10.1017/CBO9780511809477
- [8] Tversky, A. and Kahneman, D. (1992) Advances in Prospect Theory: Cumulative Representation of Uncertainty. Journalof Risk and Uncertainty, 5, 297-323. https://doi.org/10.1007/BF00122574
- [9] Plous, S. (1993) The Psychology of Judgment and Decision Making. McGraw-Hill, 1-302.
- [10] Shiller, R. (2000) Irrational Exuberance. Princeton University Press, 1-357.
- [11] Akerlof, G.-A. and Shiller, R. (2009) Spiriti Animali. Come la Natura Umana Può Salvare l'Economia. Rizzoli, 1-313.
- [12] Barberis, N. and Thaler, R. (2003) A Survey of Behavioral Finance. Handbook of the Economics of Finance. Elsevier, 1053-1128.
- [13] Kaniel, R., Liu, S., Saar, G. and Titman, S. (2012) Individual Investor Trading and Return Patterns around Earnings Announcements. *The Journal of Finance*, 67, 639-680. <u>https://doi.org/10.1111/j.1540-6261.2012.01727.x</u>
- [14] De Vries, E. and Gerber, C. (2017) The Familiar Versus the Unfamiliar: Familiarity Bias amongst Individual Investors, ActaCommercii. *Independent Research Journal in the Management Sciences*, AOSIS, 1684-1999. https://doi.org/10.4102/ac.v17i1.366
- [15] Hertz, N. (2011) Women and Banks. Are Female Customers Facing Discrimination? *Promoting Growth and Shared Prosperity in the UK*, IPPR, Institute for Public Policy Research, 1-29.
- Treichel, M. and Scott, J. (2006) Women-Owned Businesses and Access to Bank Credit: Evidence from Three Surveys since 1987. *Venture Capital*, 8, 51-67. <u>https://doi.org/10.1080/13691060500453726</u>
- Peterson, R. (1981) An Investigation of Sex Discrimination in Commercial Banks Direct Consumer Lending. *Bell Journal of Economics*, **12**, 547-561. https://doi.org/10.2307/3003571
- [18] Ogubazghi, S.-K. and Muturi, W. (2014) The Effect of Age and Educational Level of Owner/Managers on SMMEs' Access to Bank Loan in Eritrea: Evidence from Asmara City. American Journal of Industrial and Business Management, 4, 632-643. https://doi.org/10.4236/ajibm.2014.411069
- [19] Giannetti, M. and Yishay, Y. (2012) Do Cultural Differences between Contracting Parties Matter? Evidence from Syndicated Bank Loans. *Management Science*, 58, 365-383. <u>https://doi.org/10.1287/mnsc.1110.1378</u>
- [20] Ravina, E. (2012) The Effect of Beauty and Personal Characteristics in Credit Markets. Love & Loans, 1-79.
- [21] Ongena, S. and Popov, A. (2015) Gender Bias and Credit Access. ECB Working Paper Series, Vol. 1822, 1-57.
- [22] Moro, A., Wisnewski, T.-P. and Mantovani, G.-M. (2017) Does a Manager's Gender Matter When Accessing Credit? Evidence from European Data. 119-134.
- [23] Buttner, E. and Rosen, B. (1988) Bank Loan Officers Perceptions of the Characteristics of Men, Women, and Successful Entrepreneurs. *Journal of Business Venturing*,

3, 249-258. https://doi.org/10.1016/0883-9026(88)90018-3

- [24] Stevenson, D.-L. (1986) Mothers Strategies for Children's School Achievement: Managing the Transition to High School. *Sociology of Education*, **59**, 156-166. <u>https://doi.org/10.2307/2112340</u>
- [25] Orhan, M. (2001) Women Business Owners in France: The Issue of Financing Discrimination. *Journal of Small Business Management*, **39**, 95-102. https://doi.org/10.1111/0447-2778.00009
- [26] Muravyev, A. and Lehmann, H. (2012) Wiley Online Library Labour Market Institutions and Labour Market Performance. *Economics of Transition*, 20, 235-269. <u>https://doi.org/10.1111/j.1468-0351.2012.00435.x</u>
- [27] Nguyen, N. and Luu, N. (2013) Determinants of Financing Pattern and Access to Formal-Informal Credit: The Case of Small and Medium Sized Enterprises in Viet Nam. *Journal of Management Research*, 5, 240-259. https://doi.org/10.5296/jmr.v5i2.3266
- [28] Slavec, A. and Prodan, I. (2012) The Influence of Entrepreneur's Characteristics on Small Manufacturing Firm Debt Financing. *Journal for East European Management Studies*, 17, 104-130.
- [29] Fatoki, O. and Odeyemi, A. (2010) Which New Small and Medium Enterprises in South Africa Have Access to Bank Credit? *International Journal of Business and Management*, 5, 128-136. <u>https://doi.org/10.5539/ijbm.v5n10p128</u>
- [30] Abdulsaleh, A.-M. and Worthington, A.-C. (2013) Small and Medium-Sized Enterprises Financing: A Review of Literature. *International Journal of Business and Management*, 8, 36-54.
- [31] Bayer, P., Ferreira, F. and Ross, S.-L. (2016) What Drives Racial and Ethnic Differences in High Cost Mortgages? The Role of High Risk Lenders. National Bureau of Economic Research, No. 22004, 175-205.
- [32] Blanchflower, D.-G., Levine, P.-B. and Zimmerman, D.-J. (2003) Discrimination in the Small-Business Credit. *Review of Economics and Statistics*, 85, 930-943. <u>https://doi.org/10.1162/003465303772815835</u>
- [33] Storey, D. (2004) Racial and Gender Discrimination in the Micro Firms Credit Market? Evidence from Trinidad and Tobago. *Small Business Economics*, 23, 401-422. <u>https://doi.org/10.1007/s11187-004-7259-0</u>
- [34] Zarook, T., Rahman, M.-M. and Khanam, R. (2013) Management Skills and Accessing to Finance: Evidence from Libya's SMEs. *International Journal of Business and Social Science*, 4, 106-115.
- [35] Pandula, G. (2011) An Empirical Investigation of Small and Medium Enterprises. Access to Bank Finance: The Case of an Emerging Economy. *Annual Conference*, *Proceedings of ASBBS*, Las Vegas, 24-27 February 2011, Vol. 18, 255-273.
- [36] Kira, A.-R. (2013) The Evaluation of the Factors Influence the Access to Debt Financing by Tanzanian SMEs. *European Journal of Business and Management*, 5, 1-24.
- [37] Mukiri, W.-G. (2008) Determinants of Access to Bank Credit by Micro and Small Enterprises in Kenya. *Growing Inclusive Markets Conference*, 1-16.
- [38] Le, N.-T.-B., Venkatesh, S. and Nguyen, T.-V. (2006) Getting Bank Financing: A Study of Vietnamese Private Firms. Asia Pacific Journal of Management, 23, 209-227. <u>https://doi.org/10.1007/s10490-006-7167-8</u>
- [39] Andreoni, J. and Regan, P. (2008) Beauty, Gender and Stereotypes: Evidence from Laboratory Experiments. *Journal of Economic Psychology*, 29, 73-93.

https://doi.org/10.1016/j.joep.2007.07.008

[40] Olivola, C.-Y. and Todorov, A. (2010) Fooled by First Impressions? Reexamining the Diagnostic Value of Appearance Based Inferences. *Journal of Experimental Social Psychology*, **46**, 315-324. <u>https://doi.org/10.1016/j.jesp.2009.12.002</u>