“Does behavioral biases matter in SMEs' borrowing decisions? Insights from Morocco”

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DOES BEHAVIORAL BIASES MATTER IN SMEs' BORROWING DECISIONS? INSIGHTS FROM MOROCCO

Abstract

Bank financing decisions by small and medium-sized enterprises (SMEs) are crucial to their growth and survival, particularly in emerging economies such as Morocco. This study aims to assess the impact of behavioral biases on these decisions, an area little explored in the existing financial literature. The main objective is to analyze how behavioral biases such as overconfidence, risk aversion, confirmation bias, anchoring, and managerial myopia biases influence bank financing decisions of Moroccan SMEs. The approach adopted is quantitative and uses robust least squares regression to analyze data collected from 167 Moroccan SMEs. The results reveal that overconfidence and anchoring have a significant positive impact on the propensity to take out bank loans, while risk aversion and confirmation bias have a negative effect. Managerial myopia had no significant influence. Control variables such as past financial performance, the length of the banking relationship, and lower risk also positively influence the financing decision.

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INTRODUCTION

Bank loans are essential for SMEs for many reasons. Firstly, they are crucial for financing growth, enabling SMEs to invest in new infrastructure and technology without diluting their capital. Secondly, they help with working capital management, providing a solution for bridging cash flow gaps, especially for businesses with irregular or seasonal income. Finally, bank loans provide financial flexibility, enabling SMEs to react quickly to market changes or unforeseen challenges. As such, they are a vital part of SMEs' survival and growth strategy in a constantly changing economy.

Behavioral finance, a relatively recent sub-field of finance, merges concepts from psychology with conventional economic and financial theories to explain why and how individuals and financial markets often make decisions that deviate from pure rationality. Traditionally, finance has been based on the assumption that market participants are rational and that markets are therefore efficient. However, behavioral finance challenges these assumptions by introducing concepts such as cognitive biases, systematic errors of judgment, and emotional influences, which can distract individuals and markets from rationality.

Although behavioral finance has made progress in explaining many market anomalies and individual investment decisions, there is a notable lack of studies that focus specifically on the impact of behavioral biases in the bank financing decisions of businesses, particularly

SMEs. Existing research has mainly focused on investment behavior and market anomalies, leaving a gap in understanding how behavioral biases, such as overconfidence, risk aversion, confirmation bias, anchoring, and management myopia, influence corporate managers' bank financing decisions. This lack of research is particularly notable in the context of SMEs, where these decisions are crucial to the survival and growth of the business.

1. LITERATURE REVIEW

The study of capital structure decisions, in particular corporate bank lending, reveals a lack of literature on the impact of behavioral biases. Traditional models in finance, such as those proposed by Miller (1977), Myers (1984), and Jensen and Meckling (1976), explain how companies structure their capital rationally. However, behavioral finance, as highlighted by Bertrand and Schoar (2003) and Graham et al. (2013) among others, adds an additional dimension by highlighting the influence of managers' psychological biases on these decisions. These biases can lead managers to favor information that corresponds to their pre-existing beliefs, thus significantly affecting their financing and debt structure choices. Overconfidence bias is a cognitive tendency where individuals overestimate their knowledge, skills, or control over events. This overestimation often leads to an optimistic assessment of their abilities or the accuracy of their judgments. In a decision-making context, this manifests itself as excessive confidence in their own assessments or predictions, often to the detriment of objective information or external opinions. This bias can significantly influence decision-making, particularly in uncertain areas such as financial management or investment, where it can lead to risky or ill-informed choices. Overconfidence among company directors has significant implications for the demand for bank loans. According to Landier and Thesmar (2008) and Otto (2014), overconfident managers tend to favor short-term debt, reflecting excessive confidence in their ability to repay quickly. This preference can lead them to underestimate the associated risks and overestimate the company's future performance.

Furthermore, Fecht and Opaleva (2021) have shown that overconfident managers face higher loan rejection rates. This suggests that, despite the obstacles and potential rejections, these executives continue to actively seek loans, often overestimating the chances of success of their applications. Malmendier and Tate (2008) add that credit markets can be characterized by excessive lending when overconfident managers persuade lenders of their optimistic view of the business. Loss aversion and risk aversion significantly influence managers' decisions about debt and bank lending. Loss-averse CEOs favor long-term, high-risk debt, aligning their strategies with the interests of major shareholders, which may limit their willingness to take on new loans. Larsen (2006) and Brockman et al. (2010) have highlighted the importance of debt maturity in risk management. Prudent debt management can discourage new debt. In addition, Cadenillas et al. (2004) found that high debt levels increase managers' risk aversion, discouraging them from taking on more debt. Billett et al. (2007) established a link between the intensity of debt covenants and increased risk aversion, suggesting managers are reluctant to take on new debt to avoid these constraints. Jensen and Meckling (1976) observed that CEOs of highly indebted companies tend to reduce risk. At the same time, Baker et al. (2007) and Nosic and Weber (2008) have noted that loss aversion leads to overestimating risk and a preference for short-term, low-risk debt. Milidonis and Stathopoulos (2014) also highlighted the influence of risk aversion on the executive contracts and risk-taking behavior of firms, thus impacting their financing decisions and demand for new debt.

Confirmation bias, where individuals favor information that reinforces their pre-existing beliefs, plays a crucial role in business leaders' decision-making, particularly in financial risk management and bank loan applications. Costa et al. (2017) highlighted that this bias can lead managers to misjudge the risks associated with bank loans, thus increasing the likelihood of applying for loans unrealistically. Heaton (2002) and Barton and Gordon (1988) studied the impact of various behavioral biases, including optimism, risk aversion, loss aversion, and confirmation bias, on capital

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structure decisions. These biases influence preferences for debt levels and maturities, thus affecting bank lending decisions. Furthermore, Graham et al. (2013) have highlighted the importance of cultural and behavioral differences in these decisions. They cite the example of Portuguese managers, described by Hofstede (1980) as less optimistic and more risk averse than their American counterparts, which would make them less likely to seek bank loans due to their heightened loss aversion and confirmation bias. Therefore, confirmation bias and associated behavioral factors significantly impact how managers assess and manage financial risk.

Anchoring bias, crucial in behavioral finance, occurs when decision-makers rely too heavily on past experiences for their current decisions, significantly affecting financial choices, including capital structure and demand for bank loans. Although the classic models of Modigliani and Miller (1958) and Myers and Majluf (1984) emphasize factors such as profitability and growth, they do not take into account behavioral biases such as the anchoring bias. Baker and Wurgler (2002) have explored the impact of this bias, in relation to optimism and overconfidence, as shown by the work of Heaton (2002) and Malmendier and Tate (2004). Barros and da Silveira (2008) and Hackbarth (2008, 2009) have specifically analyzed how managers may favor familiar forms of finance, such as bank loans, based on their previous experiences. This dependence can increase the tendency to seek bank loans, particularly following previous positive experiences. In contexts of crisis or impending default, Elsas et al. (2014) and Dang et al. (2012) observed that firms quickly adjust their capital structure, often influenced by the anchoring bias. Byoun (2008) and Gilson (1997) suggest that companies in financial difficulty adjust their capital structure more aggressively, influenced by this bias. Leary and Roberts (2005) and Flannery and Rangan (2006) note that the decisions taken in these stressful situations are strongly marked by the anchoring bias, where managers rely on past references.

Management myopia, characterized by focusing on short-term gains at the expense of long-term performance, can significantly influence companies' financial decisions. This tendency to focus on the short term can manifest itself in a preference for immediate financing options, such as bank loans, rather than investing in more sustainable or less risky long-term financing strategies. According to Salehi et al. (2022), Daliri et al. (2020), and Zimon et al. (2022), the personality traits of managers can negatively influence company performance by favoring suboptimal financing options. On the other hand, studies by Schuster et al. (2020) and Tunyi et al. (2019) indicate a dilemma for managers between pursuing short-term profits and focusing on long-term strategies. This myopia can lead to revenue maximization in the short term, but potentially to value destruction in the long term. Managerial myopia can also be exacerbated by pay structures based on short-term results and market pressures for continued profit growth, as highlighted by studies such as Heaton (2002), Coval and Thakor (2005), and Hackbarth (2008). These structures encourage managers to focus on immediate financial results, which may result in an increased propensity to take out bank loans to finance short-term opportunities or needs, rather than seeking more strategic long-term financing solutions. Based on the literature review, 9 hypotheses have been constructed – 5 Behavioral Variable Hypotheses (*H1* to *H5*) and 4 Control Variable Hypotheses (*H6* to *H9*). The research hypotheses are given as follows:

H1: *A high level of overconfidence increases willingness to take out a bank loan.*

H2: *High risk aversion decreases willingness to take out a bank loan.*

H3: *Confirmation bias could increase willingness to take out a loan.*

H4: *Anchoring on initial experiences or information could influence the decision to take out a bank loan, either positively or negatively.*

H5: *Strong management myopia could increase willingness to take out a loan.*

H6: *Good past financial performance increases willingness to take out a bank loan.*

H7: *A long-standing banking relationship may increase willingness to take out a bank loan.*

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H8: *Company size could have a positive impact on willingness to take out a bank loan.*

H9: *A low risk score (indicating better creditworthiness) may increase willingness to take out a bank loan.*

2. METHODOLOGY

2.1. Data

The study focused on Moroccan SMEs, targeting an initial sample of 350 companies. The aim was to assess the impact of behavioral biases on their propensity to obtain bank loan finance. The data collection method consisted of using a self-administered questionnaire designed to gather detailed information on the businesses' various behavioral and financial aspects. Of the 350 SMEs contacted, only 167 have provided usable responses. This represents a response rate of around 47.7%. The reasons for this low response rate from the other companies are varied. In some cases, the questionnaires were not filled in correctly, making the responses incomplete or unusable for analysis. In other cases, company directors chose not to respond, often because of the sensitivity of the information requested, particularly concerning the financial situation and risk of the companies, even though they were assured that the questionnaires would be processed completely anonymously and for purely academic purposes.

2.2. The model and study variables

The econometric model used in the study is a multiple linear regression used to examine the relationship between willingness to take out a loan for business finance (Loan Inclination: LIN) and a set of explanatory variables. These explanatory variables are grouped into two categories: behavioral variables and control variables. In the category of behavioral variables, we have five variables. Overconfidence (OVC): This variable measures the degree of self-confidence of individuals in their financial decisions. A high score indicates high self-confidence, which can influence lending decisions by encouraging bolder behavior. Risk Aversion (RAV): quantifies the tendency of individuals to avoid risk in their financial decisions. A high score suggests strong risk aversion, which may influence cautious lending decisions. Confirmation Bias (COB): assesses individuals' preference for information that confirms their pre-existing beliefs. A high score indicates a tendency to seek information that reinforces their beliefs, which may influence their lending decisions. Anchoring (ANC): This variable measures the impact of initial information received on final decisions. A high score indicates that individuals are strongly influenced by initial information, which can play a role in loan negotiations. Management Myopia (MMY): focuses on the tendency of individuals to adopt a short-term perspective in their financial management. A high score suggests a strong focus on short-term goals, which may affect loan planning. Each behavioral variable, in addition to the variable relating to the propensity of the SME to apply for a bank loan, is measured by 5 items on a Likert scale of 1 to 5. Principal Component Analysis (PCA) was used to evaluate the score on these variables and the propensity to apply for a loan. PCA processes quantitative data to simplify the complexity of the behavioral variables and the target variable, by extracting the principal components representing the essential information from these variables.

$$
\begin{aligned}
LIN &= \beta_0 + \beta_1 \cdot OVC + \beta_2 \cdot RAV \\
&+ \beta_3 \cdot COB + \beta_4 \cdot ANC + \beta_5 \cdot MMY \\
&+ \overbrace{\beta_6 \cdot PFP + \beta_7 \cdot BRT + \beta_8 \cdot CSZ + \beta_9 \cdot CRS}^{Control\ variables} \\
&+ \mu.
\end{aligned}
\tag{1}
$$

The four control variables are: Past Financial Performance (PFP), Banking Relationship Tenure (BRT), Company Size (CSZ), and Company's Risk (CRS): Past Financial Performance (PFP), Banking Relationship Tenure (BRT), Company Size (CSZ), and Company's Risk (CRS). PFP is measured by turnover in the year preceding the survey, BRT represents the length of the relationship with the company's main bank, CSZ is a measure of the size of the company in terms of the number of employees, and CRS assesses the company's risk of bankruptcy using Altman's Z–score. The model is given by equation (1), and the variables and assumptions representing them are given in Table 1.

Table 1. Research hypotheses and variables that represent them

Hypothesis	Corresponding variable	Sense of Correlation
Behavioral variables		
H1	Overconfidence (OVC)	Positive
H2	Risk aversion (RAV)	Negative
H3	Confirmation bias (COB)	Positive/Negative
H4	Anchoring (ANC)	Positive/Negative
H5	Management Myopia (MMY)	Positive
Control variables		
H6	Past Financial Performance (PFP)	Positive
H7	Bank Relationship Track Record (BRT)	Positive
H8	Company Size (CSZ)	Positive
H9	Company Risk (CRS)	Positive

The descriptive statistics for the study variables are summarized in Table 2, providing an overview of the characteristics of the data, such as mean, median, variance, standard deviation, skewness, kurtosis, Jarque–Bera, and the associated probability.

Analyzing the correlation matrix (Table 3) for potential multicollinearity issues, the correlation coefficients between the behavioral and control variables do not appear to indicate strong correlations. Most variables have relatively low correlations with each other, suggesting that multicollinearity may not be a major concern in this dataset. However, it is important to note that the absence of high correlations in the correlation matrix does not completely eliminate the possibility of multicollinearity, particularly in regression models where nonlinear interactions or effects could be present.

Table 2. Descriptive statistics

Variable	LIN	OVC	RAV	COB	ANC	MMY	PFP	BRT	CSZ	CRS
Mean	4.0431	3.0514	3.0384	2.5782	3.1411	3.2037	117804	13.029	184.07	4.5480
Median	3.971	3.1174	3.0682	2.6203	3.1497	3.2135	1169423	13.092	186.10	4.0496
Maximum	5.5899	4.8965	4.7633	5.4431	5.4765	5.5005	245442	25.966	266.78	12.951
Minimum	2.9017	0.7221	1.4317	0.5113	0.9668	1.0048	–70616	–1.2962	96.523	2.3659
Std. Dev.	0.4522	0.7002	0.6257	0.9357	0.8975	0.9398	501941	4.5076	32.644	1.8805
Skewness	0.3900	–0.3125	–0.0850	0.1084	0.1426	–0.0515	0.0448	–0.1247	–0.1984	2.2599
Kurtosis	3.2782	3.1012	2.9343	2.8422	2.7114	2.7866	2.6100	3.2902	2.7991	9.0877
Jarque-Bera	4.7742	2.7911	0.2314	0.5003	1.1453	0.3906	1.1143	1.0192	1.3769	400.03
Probability	0.0918	0.2476	0.8907	0.7786	0.5640	0.8225	0.5728	0.6007	0.5023	0.0000
Sum	675.19	509.58	507.41	430.56	524.57	535.02	1.9E+8	2175.8	30740	759.52
Sum Sq. Dev.	33.948	81.392	65.007	145.34	133.72	146.61	4.1E+13	3372.9	176901	587.07
Observations	167	167	167	167	167	167	167	167	167	167

Table 3. Correlation matrix

Correlation Probability	DCPB	LIN	OVC	RAV	COB	ANC	MMY	PFP	BRT	CSZ
LIN	1.0000	–	–	–	–	–	–	–	–	–
OVC	0.1011	1.0000	–	–	–	–	–	–	–	–
	0.1937									
RAV	–0.0179	–0.0364	1.0000	–	–	–	–	–	–	–
	0.8185	0.6403								
COB	–0.4843	–0.0056	0.0339	1.0000	–	–	–	–	–	–
	0.0000	0.9430	0.6639							
ANC	0.1454	–0.0283	–0.0324	0.1228	1.0000	–	–	–	–	–
	0.0608	0.7170	0.6778	0.1138						
MMY	0.1138	0.0655	0.1601	0.0020	0.0084	1.0000	–	–	–	–
	0.1430	0.4003	0.0388	0.9793	0.9145					
PFP	0.2316	0.0001	0.0458	–0.0468	0.0493	–0.1746	1.0000	–	–	–
	0.0026	0.9990	0.5569	0.0483	0.5274	0.0240				
BRT	0.4273	–0.0563	–0.0044	–0.1206	–0.0831	0.1211	0.0121	1.0000	–	–
	0.0000	0.4702	0.9554	0.1205	0.2856	0.1189	0.8763			
CSZ	0.0352	0.0953	–0.1385	0.1151	0.1215	0.0800	–0.0576	–0.1448	1.0000	–
	0.6512	0.2208	0.0742	0.1386	0.1177	0.3042	0.4600	0.0620		
CRS	0.0778	–0.0452	–0.1679	–0.0728	–0.0274	–0.8862	0.1270	–0.1299	–0.0630	1.0000
	0.3173	0.5618	0.0301	0.0496	0.7251	0.0000	0.0020	0.0942	0.4184	

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3. RESULTS

3.1. OLS regression (problems of collinearity, normality of residuals, and heteroscedasticity)

Analysis of the Variance Inflation Factors (Table 4) for the OLS regression model reveals high centered VIFs for several variables indicating potential multicollinearity problems that could affect the reliability of the regression coefficient estimates. In particular, the variables Overconfidence (OVC), Risk Aversion (RAV), Management Myopia (MMY), and Company Risk Score (CRS) show centered FIVs well above the generally accepted threshold of 5 or 10. These high values suggest that these variables are highly correlated with other explanatory variables in the model, which may lead to unstable and unreliable coefficient estimates. The other variables show much lower centered FIVs, indicating a lack of significant multicollinearity with the other explanatory variables.

Table 4. Variance inflation factors for OLS

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	0.186317	288.9757	NA
OVC	0.001349	68.50318	13.019821
RAV	0.001767	66.36198	17.066589
COB	0.000792	9.229367	1.068516
ANC	0.000836	13.83869	1.038756
MMY	0.003591	120.05486	19.889653
PFP	2.70E–15	6.871669	1.050484
BRT	3.41E–05	10.03240	1.066708
CSZ	6.62E–07	35.89690	1.088224
CRS	0.000887	133.29234	14.836183

The histogram of the residuals from the OLS regression (Figure 1) shows that the data are globally centered around zero, as evidenced by the mean being extremely close to zero. However, the slightly negative median and positive skewness indicate that the distribution of residuals is slightly skewed to the right, which is a sign of non-symmetry. The kurtosis is slightly greater than 3, suggesting a slightly leptocurtic distribution compared to a normal distribution, i.e. the residuals have thicker tails and a more pronounced peak. The Jarque-Bera test gives a statistically significant result, with a probability of 0.034, indicating that the residuals do not follow a normal distribution at the 95% confidence level. This may raise concerns about applying certain statistical tests that assume the normality of the residuals in the OLS.

The results of the Breusch-Pagan-Godfrey heteroscedasticity test (Table 5) indicate a strong presence of heteroscedasticity in the residuals of the OLS regression. With a Prob. F(9,157) of 0.0004, significantly below the 0.05 threshold, the test suggests rejection of the homoscedasticity hypothesis. The Prob. Chi-Square (9) values for (Obs · R-squared) and Scaled explained SS, at 0.0387 and 0.0708, respectively, confirm this conclusion, although the latter is slightly above the standard threshold. This indicates that the variances of the error terms are not constant across observations.

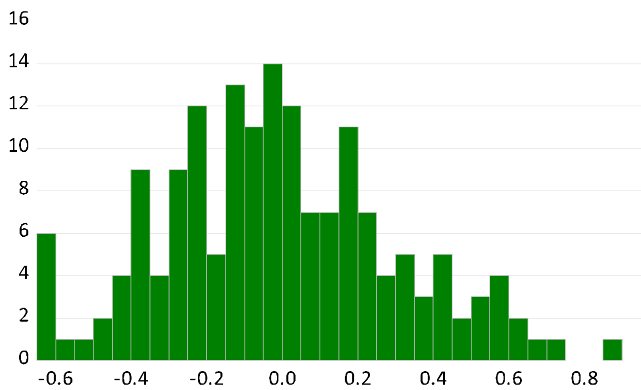

Figure 1. Normality test for OLS regression residuals

Table 5. Heteroscedasticity test (Breusch-Pagan-Godfrey) for OLS regression

F-statistic	3.559268	Prob. F(9,157)	0.0004
Obs · R-squared	17.70247	Prob. Chi-Square(9)	0.0387
Scaled explained SS	15.81521	Prob. Chi-Square(9)	0.0708

Faced with the challenges of multicollinearity, non-normality of residuals, and heteroscedasticity in the OLS model, the use of Robust Least Squares (RLS) is justified. RLS adjusts standard errors for heteroscedasticity, providing more reliable coefficient estimates even in the presence of these problems. This makes statistical tests and confidence intervals more robust and reliable, despite violations of standard OLS assumptions.

3.2. Robust least squares regression

The OLS regression model has problems of multicollinearity, non-normality of residuals, and heteroscedasticity. These problems justify the use of RLS regression. Multicollinearity, highlighted by high values of Variance Inflation Factors, can lead to instability in coefficient estimates. Although RLS do not directly resolve multicollinearity, they can provide more stable estimates in the case of moderate multicollinearity. Non-normality of residuals, detected by the Jarque-Bera test, is also a problem, as it can invalidate statistical tests based on the normality assumption. The RLS is less affected by the shape of the distribution of the residuals, offering more reliable results. Finally, the heteroscedasticity reported by the Breusch-Pagan-Godfrey test is a major concern as it can lead to biased standard errors. RLS addresses this problem by adjusting standard errors for heteroscedasticity, ensuring the validity of hypothesis tests and confidence intervals.

The Ramsey RESET test (Table 6) for RLS regression was used to assess the correct specification of the model, in particular to detect any omitted variables or errors in the functional form. The results of this test show high probability values for the t-statistic, the F-statistic, and the likelihood ratio, all suggesting the absence of statistically significant evidence of model misspecification. The t-statistic has a probability of 0.5148, indicating that there is no reason to reject the hypothesis that the model is well specified. Similarly, the F-statistic with a p-value of 0.5148 confirms this conclusion. The likelihood ratio also has a high p-value of 0.4996, reinforcing the idea that the model is correctly specified. In summary, the Ramsey RESET test indicates that the RLS model is well-fitted and has no signs of omitted variables or errors in its functional form.

Table 6. Ramsey RESET test for RLS regression

Omitted Variables: Squares of fitted values			
Test	**Value**	**df**	**Probability**
t-statistic	0.652914	156	0.5148
F-statistic	0.426296	(1, 156)	0.5148
Likelihood ratio	0.455733	1	0.4996
F-test summary			
Test	Sum of Sq.	df	Mean Squares
Test SSR	0.046069	1	0.046069
Restricted SSR	16.90467	157	0.107673
Unrestricted SSR	16.85860	156	0.108068

Analysis of the VIFs (Table 7) for the RLS regression shows that the variables in the model do not show significant signs of multicollinearity. Each explanatory variable, except for the constant C, displays a VIF centered well below the threshold generally used to indicate problematic multicollinearity, often set at 5 or 10. These low FIV values suggest that coefficient estimates in the RLS model are unlikely to be affected by high correlations between explanatory variables. Consequently, this reinforces the reliability of the regression analysis results.

Table 7. Variance inflation factors for RLS

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	0.016932	121.7904	NA
OVC	0.000294	20.69050	1.029138
RAV	0.000392	27.14287	1.098183
COB	0.000167	9.015982	1.043812
ANC	0.000180	13.84116	1.038941
MMY	0.000175	14.01461	1.104290
PFP	5.82E–16	6.853188	1.047659
BRT	7.35E–06	10.04610	1.068165
CSZ	1.44E–07	36.29517	1.100298
CRS	8.78E–05	8.825507	1.056856

The histogram of residuals for the RLS regression (Figure 2) shows that the distribution of errors is centered and relatively symmetrical. The mean of the residuals is slightly positive, and the median is close to zero, indicating a centered error distribution around the expected value. The symmetry is corroborated by a slightly negative skewness, suggesting a slight leftward bias, but not enough to cause concern,

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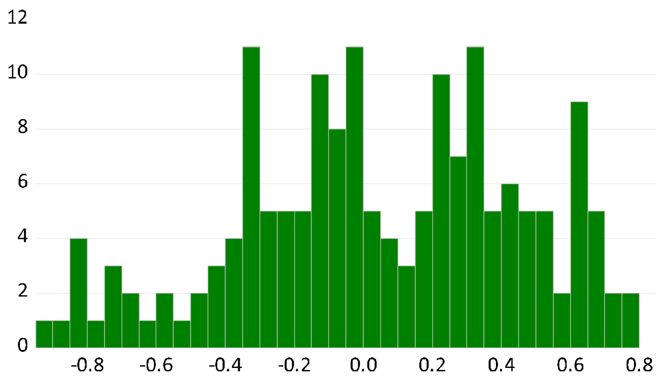

Series: Residuals	
Sample	1-167
Observations	167
Mean	0.049300
Median	0.012015
Maximum	0.911201
Minimum	-0.925134
Std. Dev.	0.413457
Skewness	-0.246402
Kurtosis	2.397927
Jarque-Bera	4.212204
Probability	0.121711

Figure 2. Normality test for RLS regression residuals

given the skewness value close to zero. The kurtosis, less than 3, suggests a flatter than normal distribution, but not excessively so. Regarding normality tests, the Jarque-Bera gives a value of 4.212204 with a probability of 0.121711, which exceeds the significance level of 0.05, implying that the distribution of residuals does not deviate significantly from normality at the 95% confidence level.

The results of the Breusch-Pagan-Godfrey test (Table 8) to detect heteroscedasticity in the RLS regression show no statistical evidence of heteroscedasticity. The probability values for the F-statistic and Chi-square tests are all well above the conventional threshold of 0.05. With a Prob. F(9,157) at 0.3252, the probability associated with the (Obs · R-squared) at 0.3189, and the probability for the Scaled explained SS at 0.2852, indicating that the null hypothesis of homogeneity of variances cannot be rejected. In other words, there is insufficient evidence that the variance of the error terms varies with the level of the independent variables, which means that the RLS estimates are probably not affected by heteroscedasticity. This strengthens the validity of statistical tests based on these regression estimates.

Table 8. Heteroskedasticity test: Breusch-Pagan-Godfrey for RLS

F-statistic	1.158836	Prob. F(9,157)	0.3252
Obs · R-squared	10.40277	Prob. Chi-Square(9)	0.3189
Scaled explained SS	10.86381	Prob. Chi-Square(9)	0.2852

On the cross-sectional analysis graph (Figure 3), the actual and fitted values appear to follow similar trends, suggesting that the regression model provides a reasonable approximation of reality. The residuals, representing the difference between the actual and fitted values, fluctuate around the zero line, which is generally a positive sign indicating that the model has no systematic bias. However, there are observations where the residuals show

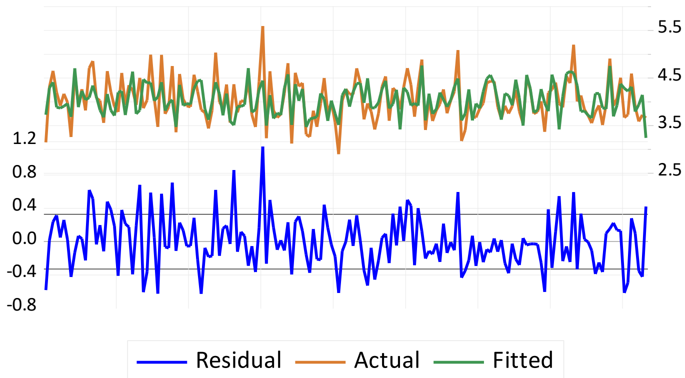

Figure 3. Cross-sectional analysis

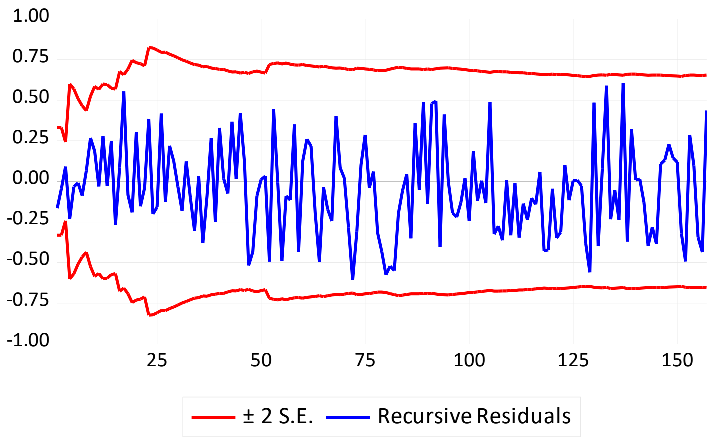

Figure 4. Recursive residuals

high peaks, indicating significant prediction errors at certain points. The absence of repeating patterns in the residuals suggests that the model does not suffer from autocorrelated errors.

The recursive residuals (in Figure 4) are the differences between the observed values and those predicted by the model, recalculated with each new observation. A stable model should have recursive residuals that vary around zero without showing trends or systematic patterns. The residuals appear to remain mainly in the +2/–2 S.E. bands, suggesting that the model is broadly stable.

The COVRATIO values (Figure 5) indicate the influence of an observation on the variance-covariance matrix of the regression coefficients. Values significantly greater than 1 or less than 1 may indicate influential points. In general, values between 0.5 and 1.5 can be considered non-influential. The graph shows variability around 1, suggesting that there may be influential observations, but most appear to be within a normal range.

The CUSUM and CUSUM of Squares tests in Figure 6 are applied to assess the stability of the coefficients of the RLS regression model. Analysis of these graphs shows that the cumulative sums of the residuals and their squares remain well within the 5% confidence limits, indicating that there is no significant structural change in the model. These results suggest that the model is stable, implying that the coefficients are constant across observations and that forecasts based on this model are reliable.

In the OLS model, problems such as multicollinearity, non-normality of residuals (Jarque-Bera test), and heteroscedasticity (Breusch-Pagan-Godfrey test) have been identified. These problems affect the reliability and accuracy of the results. The switch to RLS was adopted to counter these problems thanks to their robustness, particularly against heteroscedasticity. RLS guarantees reliable estimates of coefficients and standard errors. The CUSUM and CUSUM of squares tests confirmed the stability of the RLS coefficients, and the COVRATIO values close to 1 indicate a weak

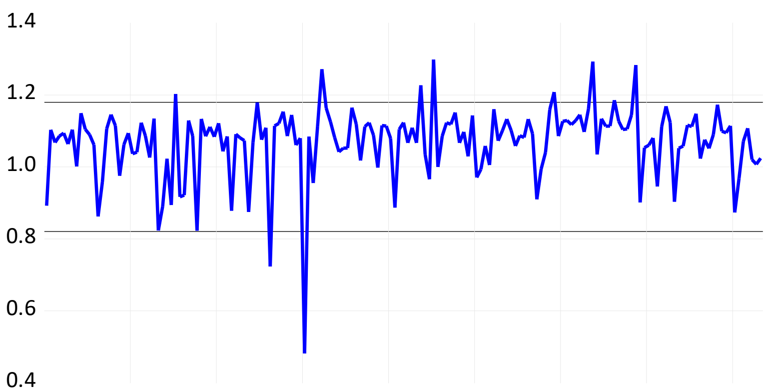

Figure 5. Influence statistics (COVRATIO)

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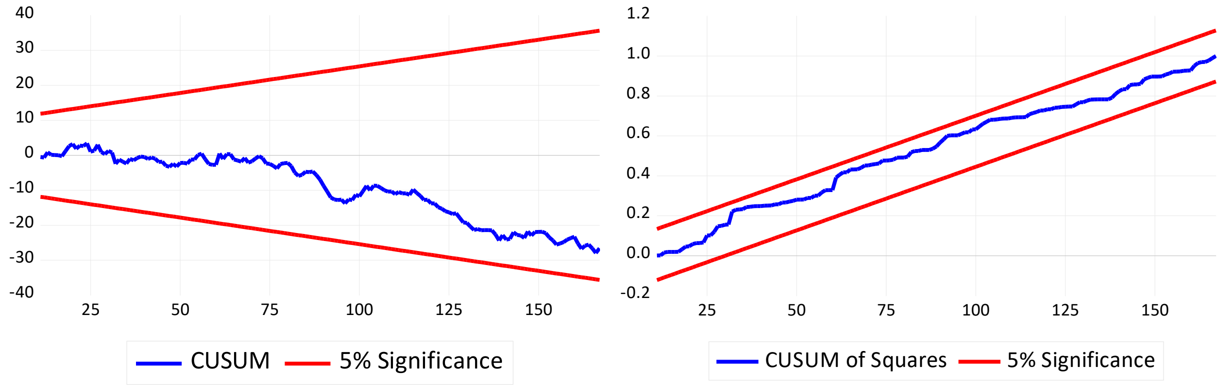

Figure 6. CUSUM test and the CUSUMSQ tests for RLS regression

influence of atypical observations. Analysis of the recursive residuals showed no significant trends, ensuring the reliability, stability, and robustness of the RLS results.

The results of the RLS regression are presented in Table 9. Hypothesis *H1*, which postulated that a high level of overconfidence on the part of the SME manager would increase willingness to take out a loan, is confirmed. The positive coefficient of overconfidence (OVC) indicates that managers with greater confidence in their own judgment are inclined to be more willing to take out a loan. Similarly, the *H2* hypothesis, according to which high risk aversion among SME managers would reduce their willingness to take out a loan, is statistically validated. The negative coefficient on risk aversion (RAV) indicates that executives with high risk aversion are less inclined to take out a loan. This negative relationship between risk aversion and willingness to take out a loan suggests that the preference for conservative financial decisions may influence the financing choice.

Table 9. RLS regression results

Variable	Coefficient	Std. error	z-Statistic	Prob.
C	2.85565***	0.43324	6.59145	0.0000
OVC	0.08781**	0.03687	2.38198	0.0172
RAV	–1.5E+01***	5.42186	–2.78451	0.0060
COB	–2.6E+00***	0.96585	–2.74314	0.0068
ANC	0.10600***	0.02903	3.65171	0.0003
MMY	0.05482	0.06015	0.91144	0.3621
PFP	1.6E+02***	43.2989	3.80325	0.0002
BRT	0.03918***	0.00586	6.68935	0.0000
CSZ	0.00066	0.00082	0.81120	0.4173
CRS	0.06571**	0.02989	2.19834	0.0293

Note: *** Significant at 1%; ** significant at 5%; * significant at 10%.

Furthermore, hypothesis *H3*, according to which confirmation bias affects willingness to take out a loan or not, is also confirmed. The negative coefficient of confirmation bias (COB) indicates that in the case of the sample, managers inclined to seek out information confirming their pre-existing beliefs are less likely to take out a loan. This suggests that confirmation bias can affect debt financing decisions. With regard to hypothesis *H4*, which suggests that anchoring on initial experiences or information could influence SME managers' decision to take out a loan, the results are in agreement. The positive anchoring coefficient (ANC) indicates that managers whose decisions are influenced by initial information are more inclined to take out a loan. This suggests that first impressions or information can be important in the financing decision. However, it is important to note that hypothesis *H5*, relating to managerial myopia (MMY), is not confirmed by the regression results. The MMY coefficient is close to zero and is not statistically significant. This indicates that SME managers who focus on short-term objectives do not have a significant impact on their willingness to take out a loan.

The results for the control variables are also consistent with the hypotheses formulated. Past financial performance (*H6*) and the length of the banking relationship (*H7*) are both significantly linked to a greater willingness of the SME manager to take out a loan. This suggests that managers whose company has a good past financial performance and a long-standing banking relationship are more likely to seek debt financing. On the other hand, company size (*H8*) has no significant effect on willingness to take out a loan, as shown by the near-zero coefficient of the company size variable (CSZ). Finally, hypothesis *H9*, which suggested that a low-risk score would increase SME managers' willingness to take out a loan, is validated, as the coefficient of the Business Risk (CRS) variable is positive and statistically significant.

4. DISCUSSION

The study explored areas that have been little studied before, drawing on existing work to formulate hypotheses. For example, it examines the impact of managers' overconfidence on their preference for debt, drawing on studies by Landier and Thesmar (2008) and Otto (2014). Although these studies did not directly address the issue of SMEs' willingness to take out bank loans, they provide a useful framework for understanding how managers' overconfidence influences financial decisions. The results of this study show that overconfidence leads Moroccan SME managers to seek bank loans. The study also examines the impact of risk aversion on the reluctance to take out loans, in line with the work of Cadenillas et al. (2004). It shows that risk aversion leads to more cautious financing choices, as evidenced by the negative correlation between risk aversion and the propensity to take out bank loans among Moroccan business managers.

For confirmation bias, although studies such as Costa et al. (2017) have not examined its direct impact on lending decisions, they have shown how this bias can lead to poor risk assessment. This study applies this notion to bank lending decisions, revealing the influence of managers' pre-existing beliefs on their financial choices. It shows a negative correlation between confirmation bias and propensity to borrow, possibly due to the negative perceptions of the CEOs in the sample. Still, it provides statistical evidence for the existence of this relationship. With regard to anchoring, although the work of Baker and Wurgler (2002) examined its impact on financial decisions in general, this study focuses on the effect of anchoring on initial experiences or information in SME managers' lending decisions. It shows that anchoring has a positive effect on loan demand in the sample studied. Again, this may be specific to the sample whose companies may have anchored themselves on negative initial experiences. Nevertheless, the study results show a significant impact on Moroccan SME managers' propensity to borrow, regardless of the sign of the correlation.

Managerial myopia, although it did not have a significant impact in this study, represents an area of divergence from trends observed in other studies. In addition, the positive correlation between financial performance and propensity to borrow suggests that companies with good financial performance are more likely to use debt financing. There is also a correlation between the length of the relationship with a bank and the propensity to obtain a loan, indicating that SME managers with well-established banking relationships are more willing to negotiate loans. The lack of any significant effect of company size on willingness to borrow challenges the preconceived notion that larger companies are more likely to apply for bank loans. Finally, the correlation between a low risk score and willingness to borrow is consistent with managers' conventional lending practices.

CONCLUSION

Making a decision to seek bank financing is part of a company's management process. Financial management is one of the essential functions in the management of a company and includes managing financial resources, including financing. Moving away from traditional models of finance, which presuppose rational and efficient decision-making, this study brings a new perspective, that of behavioral finance, revealing the impact of human behavior on financial decisions, in particular bank financing. This study attempts to bridge the gap between behavioral finance and financial management, using Moroccan SME managers as the field of analysis. The study results show that behavioral biases such as overconfidence and anchoring play a dominant role in the propensity of SME managers to opt for bank loans. These biases induce an inclination towards financing decisions that may deviate from the optimal choices suggested by conventional financial models. On the other hand, risk aversion and confirmation bias appear to limit the propensity to take out loans,

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indicating a tendency towards caution and confirmation of previous convictions. However, management myopia, a behavioral bias focused on short-term gains, does not significantly affect the financial management of SMEs.

This study opens up several avenues of research. A comparative analysis between different economic sectors or different corporate cultures could reveal variations in the impact of behavioral biases. In addition, extending the analysis to non-bank financial markets, such as equity or debt markets, could provide a more global understanding of SME financing dynamics. Another interesting avenue would be to study the interaction between behavioral biases and the structural characteristics of companies, such as size, governance structure, or the company's life cycle, to better understand how these factors jointly influence SME management financing decisions.

AUTHOR CONTRIBUTIONS

Conceptualization: Nabil El Hamidi, Khalid Ayad, Anass Touil, Khaoula Dobli Bennani.
Data curation: Nabil El Hamidi, Khalid Ayad, Anass Touil, Khaoula Dobli Bennani.
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Funding acquisition: Nabil El Hamidi, Khalid Ayad, Anass Touil, Khaoula Dobli Bennani.
Investigation: Nabil El Hamidi, Khalid Ayad, Anass Touil, Khaoula Dobli Bennani.
Methodology: Nabil El Hamidi, Khalid Ayad, Anass Touil, Khaoula Dobli Bennani.
Project administration: Nabil El Hamidi, Khalid Ayad, Anass Touil, Khaoula Dobli Bennani.
Resources: Nabil El Hamidi, Khalid Ayad, Anass Touil, Khaoula Dobli Bennani.
Software: Nabil El Hamidi, Khalid Ayad, Anass Touil, Khaoula Dobli Bennani.
Supervision: Nabil El Hamidi, Khalid Ayad, Anass Touil, Khaoula Dobli Bennani.
Validation: Nabil El Hamidi, Khalid Ayad, Anass Touil, Khaoula Dobli Bennani.
Visualization: Nabil El Hamidi, Khalid Ayad, Anass Touil, Khaoula Dobli Bennani.
Writing – original draft: Nabil El Hamidi, Khalid Ayad, Anass Touil, Khaoula Dobli Bennani.
Writing – reviewing & editing: Nabil El Hamidi, Khalid Ayad, Anass Touil, Khaoula Dobli Bennani.

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