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HEURISTICS IN THE CORPORATE CREDIT PROCESS A BEHAVIOURAL ANALYSIS OF RISK MANAGERS AND CREDIT OFFICERS

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ABSTRACT

We investigate and compare the cognitive thinking of two key actors involved in the corporate lending process: business-side credit officers and risk analysts. We investigated four different heuristics – risk aversion, overconfidence, overoptimism and representativeness bias – through a questionnaire survey based on a previous experiment by psychologists. The eight banks included in the study are among the 12 largest banks in Hungary in terms of balance sheet total, and they are also active in the financing of the large corporate segment. The respondents are relationship managers and risk analysts working in the large corporate segment. The research is exploratory and comparative and uses qualitative research methods. Based on this research, we confirmed in a banking context that the decisions of relationship managers and risk analysts are characterised by cognitive biases. One of the limitations of the research is that the decision-making process was examined in fictitious situations rather than through a real credit assessment process. The research is novel because cognitive biases have not been studied in a bank lending context specifically for credit officers and risk analysts. The results are useful for optimising decision-making processes in banks.

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1 INTRODUCTION

Theories of behavioural economics are gaining more and more importance in both business and science. Psychological studies help us understand the cognitive processes behind individual decision-making. Behaviouralists analyse economic decisions from a more realistic view of people and behaviour, in contrast to the *'Homo economicus'* of neoclassical economics. Emotional and cognitive biases have a significant impact on individual decisions, which differ from the rational choice defined by mainstream economics. These systematic biases, which typically occur in similar or identical situations, are the result of the limited cognitive abilities of the individual.

Mistaken decisions resulting from systematic cognitive thinking have also been proven to occur in financial markets. While the study of investor behaviour and the efficiency of financial markets is a popular area of research, the impact of behavioural biases on the credit decision process has attracted less attention. The investigation of the cognitive abilities of risk analysts and credit officers, which are of key importance in credit decision making, helps us understand the factors that influence the credit process.

The behavioural analysis of the credit process is a new approach that can reveal human cognitive errors that can be eliminated to make the bank credit process more efficient and reliable, which can improve the quality of the credit provided and so the profitability of the banks. The presence of the heuristics under investigation may be of great importance in credit decision making.

This study investigates corporate lending in banks from a behavioural perspective. It examines and compares the behaviour of the two key actors: credit officers (also known as relationship managers) on the business side and risk analysts on the risk management side. The research is exploratory and comparative and uses qualitative research methods. To investigate the prevalence of heuristics, experiments developed by psychologists were conducted.

The main research question is: *can heuristics such as risk aversion, overconfidence, overoptimism and representativeness bias be identified in the behaviour of credit officers and risk analysts?* On the other hand, *are there significant behavioural differences between the two actors*, and *which actor is more likely to exhibit the various heuristics*? Our research aims to answer the question of what differences in behaviour can be observed between the two groups and what might be the reasons for these differences. We did not investigate real credit process decisions, which is a limitation of our research. Another important limitation of the study is that it examines a narrow and segmented population. A snowball sampling approach was used to reach the respondents, which raises the question whether the sample can be considered representative. On the other hand, the sample size limits the scope for drawing general conclusions.

2 BEHAVIOURAL SCIENCES IN THE CONTEXT OF LENDING

Behavioural economics examines the economic decision-making and behaviour of individuals from a psychological perspective, looking for patterns of cognitive thinking behind decisions (*Kőszegi*, 2014; *Rajczy*, 2020; *Szántó*, 2011; *Cohen–Dickens*, 2002). The economic man in neoclassical economics is the 'Homo economicus', who is rational, self-interested, perfectly informed, strives to make optimal decisions, is not biased by anything and always makes the best economic decision within his/her means in order to maximise his/her utility (*Ogaki–Tanaka*, 2017; *Brzezicka–Wiśniewski*, 2014; *Golovics*, 2015; *Neszveda*, 2018). However, there are psychological factors that might constrain an individual's rational decision-making. These factors exist independently of the discipline and thus fundamentally define the scope of behavioural economics (*Rabin*, 2001). Instead of *Homo Oeconomicus*, *Homo Sapiens* is the focus of the investigation: the anomalies in the decisions of individuals as economic decision-makers, their consequences and their links to various economic phenomena (*Kovács*, 2018). A real human being, 'Homo Sapiens', is not always self-interested or fully rational and is often influenced by emotions in his/her economic decisions (Ogaki-Tanaka, 2017). The outcome of his/her decisions is influenced by social and other contexts. People may have different cognitive abilities and do not perform cost-benefit analyses before each decision. Their preferences are not fixed and usually depend on some reference point. Individuals are often unable to correctly predict their own future preferences, and they are not necessarily consistent over time but are biased towards the present. These anomalies cause biases in supposedly rational decisions (Rabin, 2001, Rajczy, 2020). Behaviourists believe that credible assumptions about human behaviour are a good starting point for analysing various economic issues (Kőszegi, 2014). Behavioural economics mainly analyses human behaviour in three areas and detects decision anomalies: how individuals evaluate possible outcomes of risky decisions, how they evaluate outcomes when they occur at different times, and how they evaluate when the outcomes of decisions affect others (Cohen-Dickens, 2002). Various psychological experiments have found biases in human behaviour. Under uncertain circumstances, individuals do not follow the principle of expected utility, but instead apply basic rules of thumb (*Hámori*, 2003; Neszveda, 2018).

Heuristics are simplifications, predictions or general rules that most often lead to an acceptable result in a given decision situation. Humans tend to rely on heuristics to make decisions, i.e., they reduce complex evaluation tasks such as probability calculations or predicting values to simpler judgements. In the majority of cases, these heuristics prove to be quite useful, but sometimes they lead to serious and systematic errors (*Tversky-Kahneman*, 1974). Heuristics are also called mental operations or 'shortcuts' in literature (Hámori, 2003). These, the *cognitive biases* or *systematic cognitive errors* that characterise human decision-making, lead to decisions that are contrary to logic and rationality. A common characteristic of these anomalies is that they are systematic, i.e., the decision-maker always falls prey to the same situation and in the same way (Tversky-Kahneman, 1974). The most common cause of simplifications is the limited, inadequate level of cognitive ability, i.e., it is unrealistic to assume that the decision-maker is capable of solving complex optimisation problems (Kahneman, 2003).

The heuristics and framing biases already identified in the study of financial markets, especially investor behaviour, may also be relevant in commercial credit markets, as they are all emotional and cognitive biases that can occur in all people. These cognitive biases can have a potentially large impact on the amount of credit or the terms on which banks extend credit to companies (*Peón–Calvo*, 2013). In addition to carrying out a complex and professional lending process, there are also a number of conflicts of interest and distortions that bank employees have to deal with when lending. One example is information asymmetries between the customer and the bank (*Walter*, 2019). In the credit market, credit officers have a critical role in assessing credit demand. Working together with risk analysts, they decide who can and cannot receive credit, and furthermore, they decide on the amount and terms of credit to be provided to a particular company. The amount and terms of the loan a company receives are determined based on their assessment. The analysis of the rationality of corporate banking raises the question of whether the people involved in the selection process have emotional or cognitive biases and, if so, how this might affect the final credit decision (Peón–Calvo, 2013).

2.1 The bank lending process

The lending decision process requires the cooperation of two areas of the bank: the business area, also called the Client Relationship Managers or credit officers, and the risk management or risk/credit analysts. The joint approval and agreement of the representatives of both areas is required for a positive decision on a loan application (Walter, 2019). Decision-making authority can differ considerably among banks. The riskier a transaction, the higher the level of the ultimate decision-maker in the banking hierarchy. In the case of corporate lending, depending on the amount of the loan, the final decision is usually made by a committee (Kovács-Marsi, 2018, Walter, 2019). The credit officer submits the loan proposal to the risk analyst, who reviews and may completeit. Risk analysts can only have a limited influence on pricing at a later stage, but they have the right to impose substantial changes to the loan amount, maturity and guarantees (Kovács–*Marsi*, 2018; Walter, 2019).

There is a natural conflict of interest and information asymmetry between a credit officer and a risk analyst. The conflict of interest arises from the fact that it is in the credit officer's interest to make the deal. The information asymmetry is because the credit officer is in contact with the client and so has more information. Risk analysts play a neutral role and are responsible for an accurate and systematic analysis of potential risks (Walter, 2019). In rating the performance of credit officers, the identified indicators are linked to positive credit decisions, which may lead to underestimating risk. An organisational culture that encourages credit extension has a negative impact on the quality of credit extended and thus on the performance of the financial institution. One solution is to keep the credit officer and the risk analysis departments separate in the banks' organisation (Peón–Calvo, 2013). In the credit decision process, there are various ways to make the two areas work together. In the case of smaller transactions, the credit officer usually has the autonomy to approve the extension of credit. In the case of larger loans, the degree of separation of the risk analyst from the client varies. Sometimes, contact with the loan applicant is strictly prohibited, while in other cases it is explicitly encouraged so that the risk analyst can get a more comprehensive picture of the client (Walter, 2016). Essentially, risk analysts are in a separate, neutral department whose function is to analyse the risk of a loan. In doing so, they basically evaluate the transaction along two dimensions: 1) the client's expected solvency and willingness to pay, and 2) the expected return on collateral.

For a corporate loan application, banks analyse the credit market at two levels. At the macro level, they analyse the economy, estimating the growth rate of the sector and its sustainability, as well as the potential level of future demand for credit. At the micro level, the client and the transaction are assessed (Peón–Calvo, 2013). The result of micro-level customer rating is the classification of companies into risk classes, usually on a 7+1 scale. The *scoring systems* are typically debt rating models developed for rating micro and small enterprises, which are based solely on objective financial data and statements to avoid subjectivity. They score the credit risk of the client by using different quantitative ratios and evaluating financial data. For medium-sized and large companies and project lending, *more complex rating systems* are used, which are supplemented by subjective assessment, to rate the credit risk of the client, and finally classify it into a homogeneous risk category (Kovács–Marsi, 2018; *Béza* et al., 2013; Walter, 2016).

In the large corporate segment, the lending process is less standardised. The complexity results from larger loan amounts and thus higher bank exposure, the lower homogeneity of transactions, and specific characteristics of the clients, e.g. the diverse and complex range of operations, mixed corporate form and specific needs. The credit and debtor risk assessment in this segment is an in-depth company evaluation. However, it is not only the risk that is higher, but also the return that can be realised on the transaction. Therefore, the analysis of these individual transactions requires more sophisticated methods and may take longer (*Virág* et al., 2013; Walter, 2016; Kovács–Marsi, 2018).

Table 1
Functions, tasks and motivation of the credit officer and the risk analyst

Credit Officer	**Risk analyst**
Functions	
Sales	Risk assessment and management
Main tasks	
– Acquisition (Customer acquisition) – Portfolio Management – Needs evaluation during face-to-face client meetings – Preliminary client risk assessment – Preparation of a proposal – Preparation of indicative offer – Loan pricing	– Risk analysis (credit, market, operational and liquidity risk) – Risk measurement – Risk exposure decision – Risk monitoring – Risk reporting
Main motivation	
– Increase the number of accredited clients or extend loans and maximise client profitability where possible	– To assess risks as objectively as possible for the clients managed and to keep credit risk at an appropriate level

Source: own edition

The task descriptions also show that risk analysts have an objective and independent role, while the credit officer may be influenced by many other external factors, such as customer relationships, personal experience, and emotions. The on-site visit and personal meetings allow the credit officer to form an opinion about the company based on his/her own impressions. Credit risk assessment is based on quantitative and qualitative analyses, with the aim of providing a completely objective valuation (Kovács–Marsi, 2018). Because of their different tasks and pieces of information, the two departments may evaluate a client differently and have different opinions about the transaction.

2.2 Behavioural issues in the lending process

Approached from a microeconomic perspective, the decision to extend or refuse credit to applicants depends on the assessment of credit officers and risk analysts (Peón–Calvo, 2013). Applying traditional economic theories to the banking context, the following can be assumed about financial institutions (*Kozma* et al., 2018):

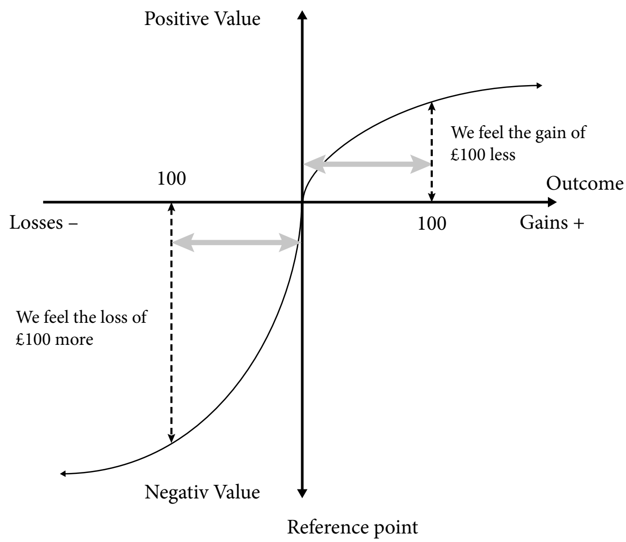
1. Banks are perfectly and fully able to assess the needs of their clients and only sell them products that perfectly meet their needs and expectations, while assessing and managing their risks.
2. Banks do not take excessive business risks, i.e., they reject market transactions whose risk exceeds the bank's risk-bearing capacity or is not covered by its capital.
3. Banks aim to maximise profits in the long term and therefore do not make financial decisions in the present that would threaten this.

Past financial crises and the losses they have caused have made financial institutions, banks, supervisory authorities and clients aware that the financial or lending market does not work perfectly (Kozma et al., 2018). The way bank employees think and behave may also be influenced by behavioural biases when deciding whether to accept or reject a loan application (*Mustilli* et al., 2018). The question arose whether behavioural biases may have contributed to the 2008 financial and banking crisis. It was suggested that positive biases about loan applications resulted in an unfavourable loan portfolio, which contributed to an increase in non-performing loans (Mustilli et al., 2018; *D'Angelo* et al., 2018).

The biases in economic decisions are caused by cognitive limitations in information processing, especially when processing large amounts of information (D'Angelo et al., 2018). Heuristics such as *availability*, *mental accounting*, the *'illusion of money'* (ignoring the effects of inflation) and the *'anchoring effect'* influence the decisions of bank employees at both macro and micro levels (Peón–Calvo, 2013). Risk aversion and related loss aversion, overconfidence, overoptimism and representativeness bias can also influence bank lending decisions. Peón and Calvo (2013), Peón et al. (2015), Peón et al. (2016) and *Hyland* et al. (2021) suggest further research on the aforementioned heuristics in the field of bank lending.

Risk aversion: *Bernoulli* (1954) attempted to show why people are risk averse in general and whether risk aversion decreases with increasing wealth for decisions with financial implications. By definition, a **risk-taker** is an individual who prefers to give up a sure thing in favour of a risk with a lower (or equal) expected value. In contrast, a **risk-averse person** prefers choices that have a certain payoff compared to a risk with a higher (or equal) expected value. According to Bernoulli (1954), individuals evaluate their prospects not on the basis of the financial expected value, but on the subjective expected value of each outcome. This subjective value or utility can be described by a concave function (representing risk-averse behaviour), illustrated in *Figure 1*.

Figure 1
Typical value function for risk-averse behaviour



Source: Thaler, 2015:31.

For example, the perceived difference between the utility of $200 and $100 in profits is greater than the nominal difference between the utility of $1,200 and $1,100. From the concave shape of the utility function (see *Figure 1*), it is clear that in two decision situations with identical expected outcomes, individuals prefer to choose the safe profit, i.e., the risk-averse option (Kahneman, 2011). Traditional economic theories argue that there is essentially no difference between the same amount of gain and loss, and that the time factor can be priced into decisions (using present value rules). However, behavioural economics has proved that people are more sensitive to a realised negative outcome than to a loss from inactivity. Individuals tend to delay decisions to avoid loss, even when they know for sure that a loss will occur. In the financial markets, this phenomenon can be observed when a stock trader tends to delay the closing of an open financial position because the immediate closing will result in a loss, even if he/she expects to suffer further losses by holding the position (Kozma et al., 2018). In the field of bank lending, this phenomenon can be observed in situations where a relatively risky client acquisition is forgone by the financial institution despite the expected high net bank income. A further example could be when, in the case of an existing client, the bank does not provide additional funding, i.e., does not increase its exposure to that client, thereby risking the maintenance of the client relationship (e.g. increasing the chances of refinancing with another bank). In the case of bank lending, it is also observed that in times of recession, or in times of mistrust and loss of confidence, which are not uncommon in the financial sector, *distortions of risk aversion* and *loss aversion* may occur. In such cases, behavioural theories may explain why bank managers are more sensitive to potential losses than to realising profits from low-risk credit operations (Peón–Calvo, 2013). In prospect theory, Kahneman and Tversky (1979) described that in cases where investors are more sensitive to losses for some reason, the dispersion of returns is not an appropriate approach to estimate risk (Kahneman, 2011). However, there is no empirical evidence that risk aversion or loss aversion has any effect on lending (Peón et al., 2016).

Overconfidence: *overconfidence* means that an individual tends to think that his/her mental and physical abilities are above average, i.e., that he/she is unreasonably confident in his/her own thoughts and abilities. When respondents' positive abilities are assessed within a given reference group, they will in most cases rate them as above average, even though, assuming a symmetric distribution, this would only be true for half of the group (Kahneman–Lovallo, 2003). Most experts also tend to overestimate their own abilities – often to an even greater extent than non-experts (*Hens–Meier*, 2016). The phenomenon of overconfidence among investors has also been observed in financial markets. Individuals tend to think that their own predictions are more accurate than they are (*Durand* et al., 2013, *Pompian*, 2016). Research has demonstrated that often those who are presumably better informed have slightly better predictions about certain things than those who have less information. By becoming more knowledgeable, one can develop an illusion of ability, a kind of *illusion of knowledge*, and can also become unrealistically confident (Kahneman, 2011). *Overconfident* actors can also develop an *illusion of control* in times of positive economic situations (Peón–Calvo, 2013). The essence of this is that individuals judge and see a positive outcome as a clear consequence of their actions, when in fact they were just lucky (Langer, 1975). Individuals with hard-to-define capabilities tend to have higher self-confidence, which may be reduced by assigning criteria to capabilities (Jáki, 2013b).

Overoptimism: the individual values the probability of positive events occurring in his/her lifetime higher than their objective probability, and underestimates the probability of undesirable, i.e., negative events (Krizan-Windschitl, 2007, Kozma et al., 2018). Empirical evidence has confirmed that people tend to attribute a higher probability to the occurrence of positive life events, such as a successful career, a happy marriage, or a long and healthy life, even when they are aware of objective probabilities such as divorce rates, etc. (*Weinstein*, 1980, Weinstein–*Klein*, 1995). When evaluating a company, the analyst may wrongly predict the probability of a company getting into financial difficulties or going bankrupt. The phenomenon of overoptimism can also be observed in the credit market. When repaying a loan, people tend to expect an improvement in their future income situation and an increase in their financial awareness rather than the opposite, although this can be diverted by a number of negative circumstances (Kozma et al., 2018).

The **representativeness bias** can be seen in several ways. According to the theory, individuals ignore the a priori probability of outcomes if event *A* is more like event *B* in terms of representativeness due to some independent factors. In other words, underlying frequency has no influence on probability estimation (Tversky–Kahneman, 1974). The individual also tends to ignore the size of the samples – in statistical terms: the population – in an uncertain judgment process, i.e., he/she is insensitive to the size of the samples, or consistently misinterprets probabilities closer in time. His/her judgements are more influenced by events that are happening now, or have happened recently, than by events that occurred further back in time (Hámori, 1998; 2003). The individual also ignores predictability. This phenomenon can also be observed when making a numerical prediction of the future profitability of a company. If an individual encounters a positive description of the company, he/she will rate its future profitability higher. If he/she reads a bad assessment, he/she will rate it lower. The mere form and quality of the description can have a strong influence on opinion formation, even without reviewing the evidence and the source (Tversky–Kahneman, 1974). In bank lending, this can occur when a bank employee with positive experiences with a particular industry, profession, or client's argumentation tends to give too much weight to good data and to underestimate risks when analysing a client's economic situation and creditworthiness (Peón–Calvo, 2013).

3 DATABASE

Our research investigates the decision-making of credit officers and risk analysts working in the field of corporate finance. In this field, each lending transaction is an individual company evaluation by the credit officer and the risk analyst. This requires the processing of a large amount of information, during which the decision-maker is more likely to apply heuristics in the evaluation. This study uses a questionnaire survey to investigate the willingness to use heuristics.

Respondents identified a set of eight banks as their current or former place of work, which are among the 12 largest banks in Hungary in terms of total assets and the size of their large corporate segments. The highest number of respondents per bank was 6 and the lowest was one employee. The questionnaire was completed over a period of 2 months from March 2022 and was entirely anonymous. The questionnaire was available and completable in electronic format, thus guaranteeing an independent response environment, free from the influence of the researchers themselves. The authors reached respondents partly through their personal contacts and partly through the LinkedIn social network. Out of a total of 26 respondents, 13 were bank loan officers and 13 were credit risk analysts. The gender distribution of respondents was 16 men and 10 women. The average age of respondents was 39, with the youngest being 25 and the oldest 61. The majority of respondents were active employees in their bank at the time of completing the questionnaire, with a total of 2 respondents stating that they were already working in another field or no longer working. The distribution of respondents in terms of experience is as follows: 27% are in junior, 65% are in senior, and 2 are in managerial positions. A total of 10 people have the authority to make decisions on their own, typically ranging from €1 million to €8 million, depending on the rating of the company proposed.

4 METHODOLOGY AND PROPOSITIONS

In our research, we tested four different heuristics based on experiments developed by psychologists.

In the first part, we examined risk aversion in the respondents' decision-making process. Our preliminary assumption, based on Bernoulli (1954), Kahneman (2011) and Pe*ó*n–Calvo (2013), was that bank employees are risk averse. *Our first proposition was that bank employees are risk averse, and the second was that risk analysts are more risk averse than credit officers.* The experiments were based on the experimental questions formulated by Kahneman-Tversky (1984). As an example, the fourth question in the questionnaire was presented as follows: *'after* *analysing two loan transactions, they had to choose one of the following options: with a probability of 92%, the bank could realise 100 000 Euros on the transaction (with a probability of 8%, the bank would not make any profit and would not incur any loss), or with a probability of 100%, the bank could realise 80 000 Euros on the transaction'.* The second option results in a secure profit, while the first option has a statistically higher expected value at risk. Statistically, the expected return from the riskier credit transaction is 92% × 100 000 + 8% × 0 = 92 000 Euro, which is more than the certain 80 000 Euro. In the first three questions, respondents had to choose between the outcomes of a fictional game of chance. Respondents could choose between a safe but lower prize and a riskier (more uncertain) but higher prize. For the other 4 questions, we put the fictional options into a banking context. The respondent had to consider the bank's point of view and choose between a client offering a safe return and a client offering a higher return but also a higher risk. The transaction may also expose the bank to losses in the event of a default by the borrower. We considered it important to place Kahneman and Tversky's (1984) experiment in a banking context, and to ask respondents to make decisions as bank employees that affect the bank's wealth.

In the second part of the questionnaire, we examined overconfidence. Overconfidence is a tendency to overestimate one's own positive abilities, i.e., to rate one's abilities as above average compared to a given reference group. Basically, an individual with healthy self-confidence will rate himself/herself above average within a given reference group. The main thing for him/her is to get a positive self-evaluation (Jáki, 2013b), so he/she tends not to consider that his/her abilities may be average compared to a given group. Therefore, if he/she thinks he/she is good at something, he/she rates it higher than average. Two experiments were used to investigate this phenomenon. In the first step, we created a list based on job advertisements available on the Internet summarising the skills required for a particular banking position (communication skills, results-oriented problem-solving mindset, conflict management, etc.). In order to make the two study groups comparable, we used the same list for both groups. In the first experiment, the respondent was asked to score his/her own skills on a scale of 1 to 7 in relation to other employees working in the same department. As an additional task, we also asked the respondents to rate the efficiency of each operational procedure compared to other departments involved in the lending process on a scale of 1-7. Our expectation was that respondents would over-rate those skills in particular that were expected for their position. Above-average ratings of these skills relative to their own colleagues as a reference group demonstrate overconfidence. Consistent with previous research (Pompian, 2016; Camerer–Lovallo, 1999; Weinstein, 1980), we hypothesised that overconfidence characterises both groups in terms of their perception of their own abilities and in that they judge the processes in which they are involved to be more effective.

In the third part, we focused on the emergence of overoptimism. Evidence for overoptimism has been demonstrated by a number of empirical studies in different situations (e.g. expectations of illness, probability of divorce for oneself versus overall divorce rate). In the process of bank lending, the loan officer's expectation is that the bank financing will be problem-free, i.e., that it will be repaid according to the terms of the loan contract. In contrast, risk management is the task of highlighting risk factors, identifying problems with loan repayment, and objectively assessing the credit proposal. Respondents were asked to think of an industry they know well and estimate (i) what percentage of companies in that industry in general will be successful in 2022 (ii) in a given industry, what percentage of companies (clients) that the bank lends to will be successful (iii) within a given industry, what percentage of firms managed by the respondent will be successful. Respondents indicated what chances of success they thought the companies in the given industry had and what they thought the success rate would be of the loans approved by them for companies in the given industry. If they are overly optimistic in their decision-making, they rate the success of the companies handled by them higher than the industry average. Based on this, **our hypothesis is that overoptimism characterises both groups, and our second hypothesis is that overoptimism is higher for loan officers.**

Finally, in the **fourth chapter, we examined the representativeness heuristic**, which is based on the fact that for basic statistical questions, such as 'what is the probability that object *A* belongs to class *B* or 'what is the probability that event *A* is a consequence of process *B*?', individuals estimate probabilities based on the extent to which *A* is representative of *B*, i.e., how similar *A* is to *B*. Individuals tend to ignore the a priori probability of outcomes. In this case, when estimating probabilities, a pre-specified baseline frequency has no effect on the response if event *A* is more similar to event *B* along some independent factor (Tversky–Kahneman, 1974). In research on the representativeness bias, we primarily investigated the disregard of the a priori, or prior probability of outcomes. In our experiment, the description of 'Adam' is one of 100 descriptions created by 70 loan officers and 30 risk analysts of themselves. Adam's description contains stereotypical traits of a risk analyst. Based on the results of Tversky and Kahneman (1974), we expect that members of both groups will ignore the baseline frequency and make their decisions based on stereotypical traits. Based on this, we formed a proposition that representativeness bias will characterise both groups when they encounter stereotypical traits. *Table 2* summarises the propositions of our study.

Table 2
Propositions

Examined heuristic	Relating propositions
Risk aversion	Credit officers and risk analysts are risk averse.
	Risk analysts are more risk averse than credit officers.
Overconfidence	The respondent considers his/her skills in his/her field to be above average.
	Respondents rate the processes of the loan application in which they are involved as more efficient than those in which they are not.
Overoptimism	Respondents rate the success of the companies the financing of which they were involved in higher than the future success of companies in the same industry.
	Credit officers are more overoptimistic.
Representativeness	Representativeness bias characterises both groups when stereotypical traits are encountered.

5 RESULTS

The risk aversion or risk appetite of risk analysts and loan officers was assessed by 7 multiple-choice questions, in which respondents chose between a certain profit and a risky investment with a higher expected reward. Our results are in line with previous research, as respondents typically chose the option with a certain outcome, thus the risk aversion heuristic prevailed. Table 3 shows the responses of credit officers and risk analysts for different questions. Respondents were risk-sensitive in 5 out of 7 questions (see 1;3;4;6;7), i.e., risk analysts and credit officers chose the event with the more certain income over the riskier one, despite the lower expected value of the certain option. The exceptions are the answers given to questions 2 and 5. For question 2, a larger proportion of risk analysts (62%) chose the riskier outcome (95% probability of a higher payout but 5% probability of a loss of 100,000 HUF), compared to credit analysts, only 38% of whom chose this option. For question 5, more than half of both risk analysts and loan officers chose the riskier option. All this suggests that, regardless of the expected value, risk appetite increases in cases where the probability of a negative event occurring is relatively lower. For questions 2 and 5 highlighted above, the probability of a negative event occurring is <= 5%, so the Bernoulli (1954) risk-value function is essentially satisfied. *The proposition that loan officers and risk analysts are risk averse is confirmed. However, the proposition that risk analysts are more risk averse than loan officers is rejected.* Consequently, if there is a disagreement between a loan officer and a risk analyst on the approval of a loan transaction, it is not because of a difference in risk appetite between two groups.

Table 3
Results of the risk aversion multiple-choice questions*

Nr	Research questions / Optional outcomes	Distribution of responses: Loan officer	Distribution of responses: Risk analyst
1.	*With a probability of 100%, you will receive a net reward of HUF 400 000* ***(EV: 400 000)***	77%	77%
	With a probability of 85%, you will receive a net reward of HUF 500 000 ***(EV: 425 000)***	23%	23%
2.	*With a probability of 100%, you will receive a net reward of HUF 400 000* ***(EV: 400 000)***	62%	38%
	With a probability of 95%, you will receive a net reward of HUF 600 000, but with a probability of 5% you will lose HUF 100 000 ***(EV: 565 000)***	38%	62%
3.	*With a probability of 100%, you will receive a net reward of HUF 400 000* ***(EV: 400 000)***	69%	54%
	With a probability of 70%, you will receive a net reward of HUF 900 000 ***(EV: 630 000)***	31%	46%
4.	*With a probability of 100%, the bank can realise a net income of 80 000 Euro on the transaction* ***(EV: 80 000)***	77%	69%
	With a probability of 92%, the bank can realise a net income of 100 000 Euro on the transaction ***(EV: 92 000)***	23%	31%
5.	*With a probability of 100%, the bank can realise a certain net income of 80 000 Euro on the transaction* ***(EV: 80 000)***	38%	31%
	With a probability of 97%, the bank can realise a net income of 100 000 Euro on the transaction ***(EV: 97 000)***	62%	69%
6.	*With a probability of 100%, the bank can realise a certain net income of 50 000 EUR on the transaction* ***(EV: 50 000)***	85%	62%
	With a probability of 98%, the bank can realise a net income of 100 000 EUR on the transaction, but with a probability of 2%, a loss of EUR 100 000 has to be written off (in the latter case no net income is realised) ***(EV: 96 000)***	15%	38%
7.	*With a probability of 100%, the bank can realise a certain net income of 40 000 EUR on the transaction* ***(EV: 40 000)***	54%	54%
	With a probability of 99%, the bank can realise a net income of 100 000 EUR on the transaction, but with a probability of 1%, a loss of EUR 300 000 has to be written off (in the latter case no net income is realised) ***(EV: 96 000)***	46%	46%

Note: *The probability-weighted expected value of the given outcome is shown in bold in brackets.

For the examination of **overconfidence**, the respondents' first task was to rate their own abilities on a seven-point Likert scale (1-7) compared to their colleagues in their field in terms of the skills listed below. In the second task, they had to rate the efficiency of different banking processes in their own bank, also on a seven-point Likert scale (1 – least efficient, 7 – outstanding performance and efficiency compared to others).

In the first experiment, the scores obtained within the two groups were averaged and are summarised in Table 4. The results show that respondents rated their own abilities above average compared to their own immediate peers, as respondents typically rated their own abilities above average within the reference group (7-point Likert scale, centre 4). No one scored 1 or 2 (i.e., less or least able). Looking at the two groups separately, it is clear that loan officers rated themselves above average in the skills required for their job (communication and interpersonal skills, assertiveness, proactiveness, results-oriented problem-solving, complex, systematic thinking, portfolio approach). Similarly, risk analysts rated analytical skills and analytical and modelling skills as above average compared to credit officers. Regarding the *'good business mindset'* competency, risk analysts rated their skills as average or below average compared to their peers, which can be explained by the fact that they are not tasked with identifying, spotting and acting on business opportunities. The majority of credit officers rated the 'business mindset' competency as above average, with an average score of 5.6, with 8 out of 13 respondents giving a score of 6 or 7 out of 13. Literature has revealed that for a skill that is difficult to define, individuals tend to rate themselves above average. This bias can be reduced by assigning criteria to the assessment of the ability (Jáki, 2013b). Our research found the same result for loan officers, but risk analysts underestimated their 'business mindset' ability even without assigning criteria.

The results confirm our hypothesis, i.e., overconfidence can be identified for both groups studied. *The study confirms the existence of overconfidence and highlights another interesting phenomenon. Comparing the results of the two groups, it can be observed that in areas more important for the position, respondents overestimate their own abilities compared to the other group.* For example, in the case of 'analytical and modelling skills', which is assumed to be a more expected (or more typical) skill for a risk analyst, this group indeed scored higher on average (mean: 5.23) compared to credit officers (mean: 4.62). Another example is that risk analysts rated their *'analytical ability'* higher (mean: 5.23) than credit officers (mean: 5.15), while *'proactivity and results-oriented problem-solving ability'* was rated by credit officers at an average of 6 on a scale of 7. This means that typically loan officers evaluate their 'proactivity and result-oriented problem-solving ability' significantly above average compared to other loan officers, and risk analysts feel, even though to a lesser extent, also above average in this ability (mean: 4.85, average would be 4).

Table 4
Examining overconfidence by assessing own abilities

Abilities/Skills	Loan officer	Risk analyst
Communication and interpersonal skills, assertiveness	**6.00**	4.92
Proactivity, results-oriented problem-solving skills	**6.00**	4.85
Complex, systematic thinking, portfolio approach	**5.77**	5.00
Conflict management, ability to compromise	**5.38**	5.23
Working in a team, cooperation with colleagues	**6.15**	5.31
Business mindset	**5.62**	4.31
Critical thinking	**5.54**	4.62
Analytical skills (operational profile, financial data)	5.15	**5.23**
Risk assessment and management	**5.15**	5.00
Analytical and modelling skills	4.62	**5.23**
His/her overall work	**5.46**	5.00

Respondents also had to assess the efficiency of the lending process. *Our expectation was that those processes in which they are involved or which were closely related to their job would be rated above the other processes in terms of efficiency.* Loan officers rated more efficient the processes in which they are involved: acquiring, negotiating, presenting, contracting. Similarly, risk analysts rated the process of 'proposing to manage risks' as more efficient than credit officers. The 'credit decision' process, in which both groups are involved, was rated as more efficient by risk analysts (see *Table 5*). Credit officers considered to be above average not only the processes related to their job, but also, e.g., assessing and estimating risks. *Overall, it can be concluded that overconfidence is a characteristic of credit officers and risk analysts, as the average is above 4 in all cases. Both groups overestimate the processes in which they are involved in lending.*

Table 5
Examining overconfidence by assessing the effectiveness of lending processes

Lending processes	Loan officer	Risk analyst
Client acquisition	**4.54**	4.15
Negotiation and communication with the Client	**5.85**	4.85
Preparing credit applications	**5.15**	4.00
Risk assessment, risk estimation	**5.85**	5.46
Proposals to manage credit risks	5.46	**5.77**
Decision process	5.38	**5.62**
Decision administration, preparation of contracts	**5.31**	4.31
Contracting with the Client	**5.38**	4.54
Loan disbursement	**5.69**	4.69

Overoptimism was investigated in two experiments. In the first experiment, we asked participants to think of an industry – or companies in that industry – about which they had extensive knowledge and experience. We asked three questions to estimate future probabilities:

- Estimate the likelihood that companies in the industry will continue to operate successfully in 2022.
- Estimate the average annual percentage of loans originated in the industry that will be successful in 2022.
- Estimate the average percentage of self-managed or proposed loans that will be successful in this industry in the coming year.

The hypothesis was that the future probability of success of the loans issued was rated higher by respondents than the future success of the companies in the industry. In other words, they ignore the objective probabilities, i.e., the success rate of the industry, when making subjective judgements about the loans they managed and issued. They underestimate the probability of possible negative outcomes in the decision-making process. *Table 6* shows that our proposition seems to be true looking at the average results for both groups. The likelihood of success for self-managed/issued loans was judged to be the most certain, with an average of 95%.

Table 6
Estimating the share of successful enterprises*

Group	Loan officer	Risk analyst	Total
Successful companies in a given industry	89.00%	88.75%	88.88%
Successfully operating companies in a given industry that have received bank loans	92.69%	92.31%	92.50%
Success rate of firms managed by the respondent in a given industry	96.46%	93.77%	95.12%

Note: *By success, we mean that the company's debt service is problem-free in 2022.

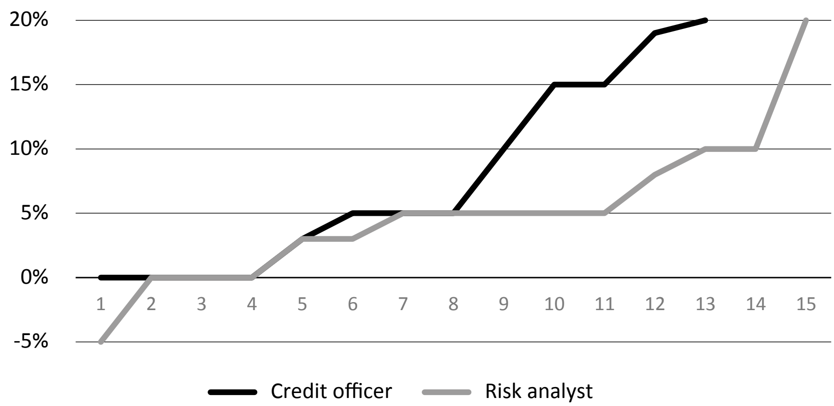
Comparing the two groups, credit officers are more optimistic, with higher average scores for all three questions compared to the risk analysts' answers. *Figure 2* shows that, compared to successful firms in the industry, credit officers rated the success of loans in the industry 7 percentage points higher on average, with a 7 percentage point deviation, while risk analysts rated the success of loans in the industry only 5 percentage points higher, with a 6 percentage point deviation. Despite both groups being characterised by overoptimism, the two lines in *Figure 2* show how much higher respondents rated the success of the firms they managed compared to the perceived proportion of successful firms in their industry. As can be seen from the line graph, risk analysts (grey line) were less overoptimistic, i.e., they perceived the clients which they managed themselves less successful than the credit officers (black line). The difference is explained by the representativeness heuristic discussed below. In short, risk analysts typically do not meet the client, so their judgment is not distorted by a subjective element. Conversely, credit officers are in contact with the client, so they may develop trust and sympathy, which can facilitate the development of an overly optimistic outlook on the future.

Figure 2
Overoptimism test results

The difference between the respondents' perceived success in the industry and the perceived success of the firms they finance in the industry

	Loan officer	Risk analyst
Average	7%	5%
Max	20%	20%
Min	0%	–5%
Deviation	7%	6%

How much higher is the perceived likelihood of success for the credited firms than the perceived likelihood of success for the industry (in ascending order of difference)



In sum, overoptimism prevails in both groups, but to a higher extent in the case of loan officers, as shown in *Table 6*, who rate the future success of their own loans higher than the average success rate for the industry. With a higher number of items, it would also be possible to examine whether the difference is statistically significant. One reason for the lower future optimism of risk analysts is that they do not meet the client, so their objective value judgements are not distorted by subjective stereotypical traits, for which the representativeness heuristic is responsible.

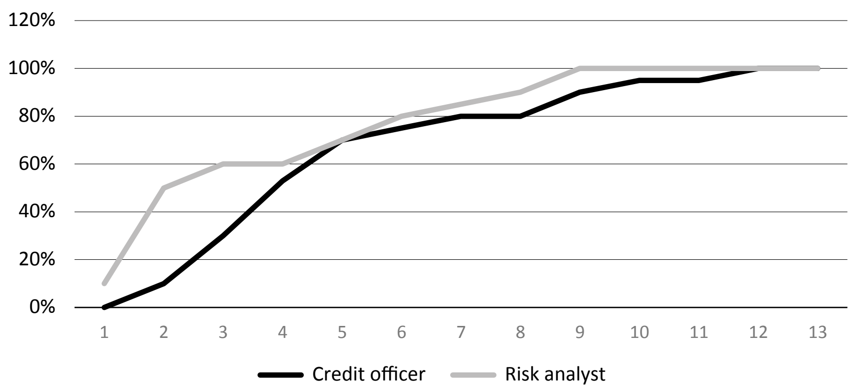
When testing **representativeness heuristics**, respondents were given the following information on a priori probabilities: '*In an experiment, 100 bank employees, 70 loan officers and 30 risk analysts were asked to give a short description of themselves*'. Respondents were asked to estimate the probability that the following randomly selected person description belonged to a loan officer or a risk analyst. The description shows the personality traits of a stereotypical risk analyst: *'Adam, 35, married with two children. He is extremely thoughtful and organised in his daily life. He analyses every situation carefully before making any decision. He is not a very sociable person, he is cautious in building relationships, but he is able to give very good advice.*' Based on Tversky–Kahneman's (1974) experiment, we expected that both groups would be more likely to attribute the person description to a risk analyst than to a credit officer, ignoring the baseline frequency given. That is, the probability is determined by the extent to which the description of 'Adam' is representative of the stereotype of the credit officer or risk analyst, the characteristics, notions and prejudices associated with the position, and objective probability, that only 30% of respondents were risk analysts, is not taken into account. The results shown in *Figure 3* confirm the representativeness heuristic for both credit officers and risk analysts. Respondents were asked to estimate the percentage probability that Adam was a loan officer or a risk analyst. The response 'definitely a risk analyst' was higher for the risk analysts surveyed than for the credit analysts, as shown in the line graph in *Figure 3*. The representativeness heuristic was more pronounced for risk analysts, with respondents being more likely to say that Adam was a risk analyst (grey line), as stereotypical risk analyst traits were present in Adam. Overall, a risk analyst is more confident (overconfident) in recognising a risk analyst's personality. Also from the line graph, it can be seen that five of the risk analysts gave a probability of 100% that the persona belongs to a risk analyst (whereas the objective probability is 30%), while only two of the credit analysts gave a probability of 100%.

Figure 3
Representativeness heuristics test results

'Adam' is a stereotypical risk analyst's description.
How likely is he to be a risk analyst/credit officer in a population where 30% are risk analysts and 70% are credit officers?

	Loan officer	Risk analyst
Adam is a credit officer (credit officer has a priori probability of 70%)		
Average	32%	23%
Deviation	35%	28%
Adam is a risk analyst (risk analyst has a priori probability of 30%)		
Average	68%	77%
Deviation	34%	28%

Per respondent, judgement that 'Adam' is likely to be a risk analyst (in ascending order of likelihood)



In sum, our proposition on the representativeness heuristic is confirmed because the stereotypical traits of the risk analyst in the description of 'Adam' distracted respondents' attention from the baseline frequency. Tversky and Kahneman (1974) reported similar results in their experiments, so the results of our study are consistent with previous research. Both loan officers and risk analysts overlook basic frequency in case of stereotypical traits, which is more pronounced during client meetings than when merely studying documents. The results of the overoptimism and representativeness heuristics suggest that it is particularly useful and necessary to create a 'firewall' between risk analysts and clients to reduce representativeness heuristics and thus mitigate the overoptimistic outlook of particular clients.

A summary of our propensity score is presented in *Table 7*. Out of the seven propositions tested, six were accepted and one was rejected, as we found no difference in risk appetite between risk analysts and loan officers.

Table 7
Summary of the evaluation of the propositions

Examined heuristic	Relating propositions	Conclusion
Risk aversion	Credit officers and risk analysts are risk averse.	✓
	Risk analysts are more risk averse than credit officers.	×
Overconfidence	The respondent considers his/her skills in his/her field to be above average.	✓
	Respondents rate the processes of the loan application in which they are involved as more efficient than those in which they are not.	✓
Overoptimism	Respondents rate the success of the companies the financing of which they were involved in higher than the future success of companies in the same industry.	✓
	Credit officers are more overoptimistic.	✓
Representativeness	Representativeness bias characterises both groups when stereotypical traits are encountered.	✓

6 SUMMARY

Our questionnaire survey investigated the prevalence of 4 heuristics in the context of bank lending through experiments among loan officers and risk analysts. The four heuristics examined were *risk aversion*, *overconfidence*, *overoptimism*, and *representativeness bias*. The main findings of our research are that risk-averse behaviour characterises both credit officers and risk analysts, with both groups choosing the less risky outcome despite the lower expected value. The study suggests that risk analysts are not more risk averse than loan officers. The difference of opinion between the two groups on the evaluation of a transaction or client is not due to risk sensitivity, but rather can be explained by the different roles and the resulting different motivational factors, such as bonus targets. Overconfidence was confirmed by two experiments. On the one hand, respondents in both groups rated their abilities required for their own position, which showed that both groups were characterised by a healthy confidence, so-called 'overconfidence', in their abilities to perform the tasks in their field, as they rated their abilities as above average compared to their colleagues. On the other hand, both groups rated those bank lending processes more effective in which they were involved or which were closely related to their job. Overall, along the lines of their belief in their abilities and their assessment of the effectiveness of their work, we found, in line with the results of previous research, that two important actors in the loan appraisal process are also characterised by overconfidence. We confirmed overoptimism with two experiments. On the one hand, respondents rated, on average, the probability of success of their loans higher than the probability of success of firms in their industry. Our research also showed that loan officers' optimism about the success of loans is higher than that of risk analysts. One reason for this is that loan officers meet the client, gain personal impressions, develop sympathy and trust. This is why it is common practice in a significant number of commercial banks not to allow risk analysts to meet the client. Our next experiment examined the representativeness heuristic. Complementing the results of the previous experiment, we demonstrated that both groups can be characterised by the representativeness heuristic to almost the same extent.

In summary, our research investigated the decision-making of credit officers and risk analysts involved in corporate lending and demonstrated the presence of four heuristics in their decision-making processes. Our main findings are that the two groups are characterised by risk aversion, overconfidence, overoptimism and representativeness heuristics. Based on the results, we confirm that it is good and applicable practice for the risk analyst to be separated from the client by a 'firewall' and to be allowed to assess the credit applications based only on the data and material presented to them. A further important finding is that the conflict of interest between the loan officer and the risk analyst is not caused by a difference in risk appetite, rather it can be explained by the different incentive systems resulting from the different positions. The incentive scheme for loan officers encourages granting as many loans as possible, whereas the incentive scheme for risk analysts does not – and cannot – include this. Due to the representativeness heuristic resulting from the personal contact and the three other heuristics demonstrated in the research, the credit officer overestimates the probability of positive outcomes and underestimates the probability of negative outcomes when evaluating a loan transaction to a greater extent than the risk analyst. The research could be extended to investigate other biases such as bounded rationality, mental accounting or the framing effect, which would help us understand the biases in lending more thoroughly.

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