SCHOOL OF ECONOMICS AND MANAGEMENT
LUND UNIVERSITY

Department of Business Administration

Bachelor Thesis - Business & Data Analytics

FEKH39

Autumn 2021

Expect the Unexpected

Measuring Noise & Bias in the Credit Assessment Process

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Titel	Expect the Unexpected - *Measuring Noise & Bias in the Credit Assessment Process*
Seminariedatum:	14/1-2022
Kurs:	FEKH39, Examensarbete på kandidatnivå i Business & Data Analytics, 15 högskolepoäng
Författare:	Leonard Ekberg, Pontus Govenius, Jacob Skoglund
Handledare:	Hans Knutsson
Nyckelord:	Kreditgivningsprocess, Kredithandläggare, Beslutsfattande, Bias, Noise
Forskningsfråga:	Till vilken grad påverkar *Bias* kredithandläggare bedömning av bolåneansökningar? Samt hur mycket *Noise* finns det i processen?
Syfte:	Att mäta Bias påverkan på kredithandläggares beslutsfattande vid kreditbedömning av bolån och mäta nivån av noise som finns i processen
Metod:	Uppsatsen tillämpar en kvantitativ, deduktiv och fallstudiemetod för att testa fyra hypoteser baserad på teoretisk kunskap om mänskligt beslutsfattande relaterat till koncepten bias och noise. Data samlades in från 15 kredithandläggare som arbetade på tre olika Handelsbanken kontor och som svarade på en enkät baserade på fiktiva bolåne ansökningar. Insamlad data analyserades genom att använda ett *oberoende t-test* och ett *relativt approximations fel* för bias respektive noise.
Teoretiska perspektiv:	Uppsatsen applicerar existerande teoretiska ramverk gällande mänskligt beslutsfattande samt koncept relaterat till bounded rationality, bias och noise
Resultat:	Vi fann att höga nivåer av *noise* existerar inom kredithandläggares bedömningar vilket påverkar deras beslutsförmåga avseende beviljade krediter, den givna räntan och den upplevda risken bland ansökningarna. Dessutom illustrerar resultaten att *bias* påverkar kredithandläggares beslutsfattande, där socialt mindre prestigefyllda yrken upplevs mer riskfyllda jämfört med sökande med mer prestigefyllda yrken.
Slutsats:	Bias påverkar delvis kredithandläggares beslutsfattande vid bedömning av ansökningar om bolån, medan *noise* är utbrett bland kredithandläggare såväl som mellan enskilda kontor.

Title Expect the Unexpected - *Measuring Noise & Bias in the Credit Assessment Process*

Seminar date: 14/1-2022

Course: FEKH39, Degree Project, Business Administration, Undergraduate level, 15 University Credit Points ECTS

Authors: Leonard Ekberg, Pontus Govenius, Jacob Skoglund

Advisor: Hans Knutsson

Keywords: Credit assessment, Loan officer, Decision-making, Bias, Noise

Research questions: To what extent does bias impact loan officers' decision-making upon assessing mortgage credit applications and what level of noise is embedded within the process?

Purpose: To measure what extent bias impacts loan officers decision-making upon assessing mortgage applications and the level of noise embedded within the process

Methodology: The thesis applies a quantitative, deductive, and case study approach to test four hypotheses based on theoretical knowledge regarding bias and noise. Data were collected from 15 loan officers working at three different branches at Handelsbanken answering a questionnaire based on fictional mortgage applications. The data were further analyzed by using an *independent t-test* and *relative approximation error* for bias and noise respectively.

Theoretical perspectives: The theoretical framework that the present thesis applies relates to the theories explaining human decision-making as being characterized by bounded rationality and the concepts of bias and noise.

Results: We found large levels of noise within loan officers' credit assessments that impact loan officers' decision-making capabilities regarding credit granted, the interest rate given, and the risk perceived with the applications. Furthermore, the findings illustrate that bias impact loan officers' decision-making, where applicants with socially less prestigious occupations are perceived as riskier relative to applicants with more prestigious occupations

Conclusions: Bias does partially affect loan officers' decision-making upon assessing mortgage credit applications, while noise is prevalent amongst loan officers as well as between individual branches.

Abstract

The purpose of the thesis is to measure how bias impacts loan officers' decision-making upon assessing mortgage applications and the level of noise embedded within the process. Quantitative data were collected from 15 loan officers working at three different branches at Handelsbanken answering a questionnaire based on fictional mortgage applications. The statistical analysis used an unpaired t-test and the relative approximation error to assess bias and noise respectively. We found large levels of noise within loan officers' credit assessments that impact loan officers' decision-making capabilities regarding credit granted, the interest rate given, and the risk perceived with the applications. Furthermore, the findings also illustrated the impact of bias as loan officers perceive applicants with socially less prestigious occupations as riskier than applicants with socially considered more prestigious occupations. The theoretical contributions of this study further enhance our understanding of human decision-making and more specifically how and to what extent bias and noise impact the credit assessment process. The main implications of these findings are that households that are applying for a mortgage can likely expect large variations in the amount of credit they can borrow and at what interest rate. Additionally, the empirical findings imply that loan officers' assessment of the applicant's creditworthiness can be viewed as subjective despite relying on standardized credit policies.

Keywords: mortgage, credit assessment, loan officer, decision-making, bias, noise

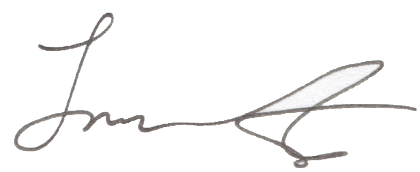
Word count: 13 504

Acknowledgments

First and foremost, we would like to extend our heartfelt gratitude to Hans Knutsson, Senior Lecturer at the Department of Business Administration at Lund University School of Economics and Management. In his role as our supervisor in writing this thesis, he has given us valuable insights and advice that has increased the quality of this thesis. Secondly, we would like to thank Hans Knutsson and Anna Thomasson for having introduced the course in Business and Data Analytics to the School of Economics and Management this year. An area that is believed to become increasingly more important going forward. Thirdly, since this is our last course, we would like to express our gratitude towards the School of Economics and Management at Lund University and all the lecturers, employees, and peer students encountered throughout the years. Last but not least, we would also like to extend our gratitude towards the loan officers and branch managers at Handelsbanken who participated in the study and for giving valuable insights on how to adjust and improve the quality of the questionnaire that was used for data collection in the thesis.

Pontus Govenius

Leonard Ekberg



Jacob Skoglund

Lund, January 11, 2022

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List of Concepts

Branch - a particular office constituting a part of the bank's organizational structure.

Credit assessments - Loan officers collect data about the borrower to assess the creditworthiness, i.e. the applicant's ability to repay the debt, and thereby decide whether to accept or reject the application.

Mortgage - A credit where the lender has a legal claim of the underlying property which is realized if the borrower fails to repay the loan.

Bias - Human irrational beliefs that disturb the capability to make accurate decisions with regards to facts and evidence.

Noise - Professionals upon facing identical cases showing inconsistency in their decision-making.

Framing effects - A cognitive bias stating that people's choices are largely influenced by the way that options are presented.

Heuristics - People's reliance on Rules of thumb when solving problems, although being useful, subsequently causes people to make predictable errors or systematic biases.

Relative approximation error - Consider the relative difference between an individual answer and the mean in percentage.

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1 Introduction

This chapter aims to provide a thorough understanding of the background to the thesis, followed by a problematization of the research subject and a description of the research purpose. Lastly, the outline of the thesis is presented.

1.1 Background

Simon (1955) introduced the concept of bounded rationality where humans' limited cognitive capabilities explain their tendency to solve problems by selectively collecting data and the tendency to stop upon finding satisfying solutions, i.e. good-enough. This stood in contrast to traditional neoclassical economics which postulates that decision-makers collect all information and assess all potential solutions (Simon, 1955). Simon (1979) argued for economic research to generate more practical knowledge during his lecture upon receiving the 1978 Nobel Prize in Economic Sciences. He proposed economic researchers to stop theorizing that decision makers are perfect rational “homo economicus” and instead postulate them as being bounded rational “homo sapiens”. This inspired additional research with the purpose of further illustrating anomalies to existing paradigms which later on laid the ground for behavioral economics and viewing biased decision-making as rules rather than exceptions (Kahneman, Knetsch & Thaler, 1991).

As an effect, Kahneman and Tversky (1979) introduced prospect theory, which played a vital part in illustrating people's reliance on heuristics, i.e. rules of thumbs, as although being useful upon facing complex problems, subsequently causing people to make predictable errors referred to as systematic biases. The insight that decision-makers make predictable rather than random errors was decisive since it made arguments that describe bounded rationality as being caused by random errors, that were canceled out on average, were no longer being viewed as valid (Thaler, 2018). Consequently, bias is a term that has been researched in close connection to humans’ ability to make decisions. Its meaning can be described as our irrational belief that disturbs our capability to make accurate decisions with regard to facts and evidence (Das & Teng, 1999). For most people, the term bias is associated with the human incapability to make fair and unbiased decisions and is therefore regarded as something negative. However, Johnson, Blumstein, Fowler, and Haselton (2013) argue that bias actually can enhance our decision-making capacity. They acknowledge that bias can lead us to make mistakes, but on the other hand, that bias also can steer us away from making mistakes that could be more costly.

Executives and professionals in organizations are dealing with similar tasks repeatedly and are expected to treat these tasks and decisions similarly. Identical cases should not have different outcomes depending on one's current mood or which day it is. However, humans are unreliable decision-makers and are strongly influenced by these factors when making decisions, which is what is referred to as *noise* (Kahneman, Rosenfield, Gandhi & Blaser, 2016). There are differences between noise and bias, even though one might think they are similar. To elaborate, by being biased you repeatedly make inaccurate decisions that are in favor of a specific outcome. If you are noisy you consistently make inaccurate and inconsistent decisions on similar cases that cannot be explained (Kahneman et al. 2016). See Figure 1 below that illustrates how bias and noise affect decision-making accuracy. Kahneman et al. (2016) explain that the level of noise existing within organizations usually is higher than expected. In considering this, it might not be surprising that Mintzberg and Waters (1985) have shown that organizations' intended strategies are only partially translated into actually realized strategies due to inconsistent and in some cases biased decision-making.

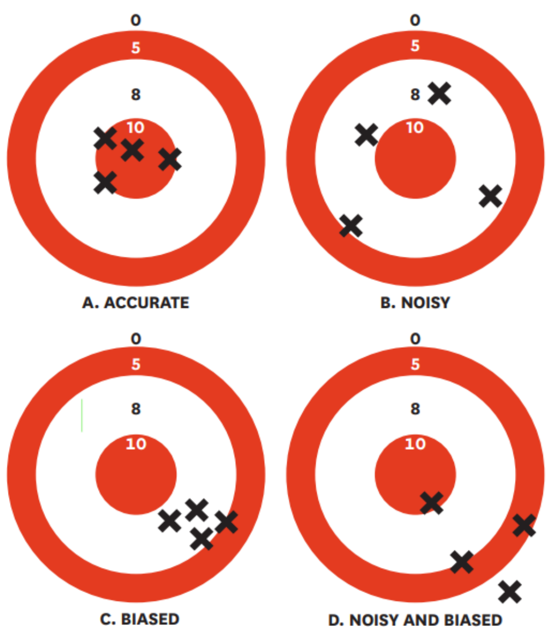


Figure 1: Illustration of how bias and noise affect the accuracy of decision-making (Kahneman et al. 2016).

1.2 Problematization

Problems related to noise and bias can partly be solved by replacing human judgment with algorithmic-driven decision-making processes, although this might not be suitable for situations relying on idiosyncratic data and requires negotiation with the counterparty (Kahnemen et al. 2016). In acknowledging that bias and noise do impact decision-making, organizations might benefit from having tools that identify and measure the impact of bias and the level of noise existing within different processes (Milkman, Chugh & Bazerman, 2009). This can be translated into enabling people to make decisions more aligned with the ones they would have made if they were fully aware of their biases (Thaler, 2018). Also, from an organization's standpoint, it could be viewed as reducing potential gaps between intended- versus realized strategies. The reasoning is in line with previous research which argues that since we have a fairly good understanding of how bounded rationality impacts decision-making, researchers should increasingly aim to use this knowledge to enhance processes that are relevant for organizations (Milkman et al. 2009).

The reasoning is further strengthened by previous research concluding that empirical evidence on the ways bias impacts individual decision-making in different industries is lacking (Barberà-Mariné, Cannavacciuolo, Ippolito, Ponsiglione & Zollo, 2019). The question one could ask is why cognitive bias and noise is an important factor to analyze and understand in organizations? The most common answer and description is given from the definition made by Barberà-Mariné et al. (2019) who describes bias as "useful measurements for detecting process improvement actions" (p. 2890). The problem and what is interesting for organizations is not the ability to recognize the existence of bias and noise per se*,* it is rather enabling methodologies with the ability to measure the level of impact and thus, be able to recognize when the levels exceed thresholds of what is deemed as acceptable levels (Kahneman et al. 2016). The topic's relevance is evident based on previous descriptions of organizational decision-making, implying that bias and noise do have a high unconscious impact on organizations' ability to make rational decisions. Most decision-making processes incorporate bias, but also noise (Kahneman et al. 2016). Especially in decision-making processes involving human interaction, where a company's strategy is based on a close, relationship-based ground with the customer. (Trönnberg & Hemlin, 2012).

One vital decision-making process for individual households and the overall economy is the issuance of mortgage credit, most often being the largest transaction in one's lifetime. The importance becomes evident during crises, nonetheless during the 2007-09 financial crisis partly explained by mispricing of risk within US mortgage debt (Berger, Molyneux & Wilson, 2019). In the cases where households apply for a mortgage, loan officers decide to accept or reject the application based on assessing the applicant's creditworthiness - being the ability to repay the credit (Swedish FSA, 2020). Previous research has shown that bias and noise exist within credit assessments. Deakins and Hussain (1994) illustrated that whether or not credit is granted depends largely on which loan officer or branch manages the application. Although, as Trönnberg and Hemlin (2012) point out, research in the area is limited. Previous research has not specified the level of impact that bias and noise have on the outcome of credit assessments, that is, the impact on loan officers' decision-making regarding volume credit granted and interest rate given. Additionally, it has not specified the level of noise embedded in the process.

1.3 Research Purpose

Based on the research background and problematization, the purpose of the present study is to measure if bias affects loan officers' mortgage credit assessments and to measure the level of noise embedded within the process.

1.4 Outline of the Thesis

The thesis is divided into seven parts. Chapter 1 consists of an introduction to the thesis, which then continues with the problematization and the research purpose. Chapter 2 continues with a literature review that incorporates the theoretical framework surrounding topics related to decision-making, bias, noise, and credit assessment, ending with presenting the formulated hypotheses. Afterward, the methodology for the study is described and argued for in Chapter 3. The results of the present thesis are presented in Chapter 4, followed by an analysis in Chapter 5. Conclusions are drawn in Chapter 6 and lastly, Chapter 7 provides a discussion followed by a recommendation for future research.

2 Literature Review

This chapter provides the theoretical framework upon which the present thesis research purpose and hypothesis are built upon. Firstly, the section presents previous research findings related to human decision-making, bias, noise, and credit assessments. Secondly, the literature review is summarized and lastly, the present study's hypotheses are presented.

2.1 Human Decision-Making

Understanding human judgment and decision-making is vital when trying to understand human behavior (Andersson, 2001), therefore this section gives an overview of relevant research in this area. Scholars have defined decision-making processes in terms of being rational, linear, and analytical (Cabantous & Gond, 2011). However, since cognitive bias affects the information that is gathered during the process and later influences our decisions, other views have been lifted describing decision-makers as being "boundedly rational" (Simon, 1955), or as "quasi-rational" (Schrivastava & Grant, 1985). These different views have been translated into a debate amongst economic researchers, where some argue for replacing the neoclassical views of decision-makers being perfectly rational in favor of postulating from them being less rational and hence, achieving more realistic descriptive models and increasing their explanatory value (Thaler, 2000).

On the topic of trying to understand decision-making, Simon (1978) argued for the importance of taking into account the vast number of factors influencing the process and the limited cognitive resources humans possess. This results in humans having different focus areas in where and what information they should gather and process upon trying to solve complex problems. Therefore, in trying to understand the rationality inherent in decisions, it is essential to focus on the processes underlying decisions rather than explicitly focus on outcomes. Hence, Simon (1978) argued for increased usage of existing knowledge and tools from other social sciences like psychology, to increase the explanatory value of decision-making theories within the field of economics.

To alleviate and make complex problems tolerable, humans use heuristics when evaluating and collecting data. Tversky and Kahneman (1974) describe heuristics as rules of thumb that are useful but also cause people to make systematic biases and that the use of heuristics is often done unconsciously. One example is people's reliance on *availability heuristics,* which is assessing risk based on how easy they recall similar instances that have happened, rather than by assessing risk based on the actual probability of the outcome. Furthermore, people rely on *anchoring heuristics* – that is disproportionately relying on pre-existing information (Tversky & Kahneman, 1974).

To further elaborate on the difficulty of trying to understand human decision-making, Simon (1991) highlights the importance of considering the organizational impact, since individual learning depends on the existing knowledge possessed by other individuals and the information existing within organizations. Simon (1991) argues that this can be viewed as internal learning, making decision-making a social process, where information is exchanged between individuals or groups of individuals. Other research states that the social environment and context have a significant impact on individual decision-making, for instance through social learning and peer pressure (Bruch & Feinberg, 2017). People adapt towards others' behaviors through descriptive norms and social cues which provide information about what is appropriate behavior, where the effect on one's behavior becomes stronger the more similar and comparative the situation is to one's own (Bruch & Feinberg, 2017). Thaler (2018) means that, when trying to understand decision-making, it is hard to draw accurate conclusions by examining isolated events. One rather benefits from using multiple data sets consisting of decisions and outcomes, which makes it more straightforward to analyze decision-making processes that occur frequently. Although, this is easier said than done since most organizational processes are not observable for outsiders (Thaler, 2018).

Kahneman and Tversky (1979) suggested prospect theory for explaining human decision-making under uncertainty. The model illustrates that people's decision-making is impacted by the certainty effect and loss aversion, meaning people emphasize certain outcomes too much relative to probable outcomes and are risk-averse while facing gains but risk-seeking while facing losses. This in turn explains why people, upon facing losses, are more likely to accept risk levels that otherwise are viewed as unacceptable (Kahneman & Tversky, 1979). Another important insight from the prospect theory is that people view outcomes in terms of gains and losses, defined to a neutral reference point (Kahneman & Tversky, 1979). The starting point or location of the reference point is influenced by the framing of the situation. Thus, an outcome in one situation or “frame” might be perceived as a gain whereas the same outcome might be perceived as a loss in another (Tversky & Kahneman, 1981). To exemplify, if a situation is framed in terms of a survival rate of 90% rather than as 10% risk of death, people will interpret the situation differently which affects their decision-making. This means one can change people’s preferences when facing a problem by changing the frame of the present situation (Kahneman & Tversky, 1984). Additionally, framing is controlled by factors such as the decision-makers’ expectations, norms, and habits (Tversky & Kahneman, 1986). Hence, framing can be viewed as determining how people perceive the world, thus the use of narrow frames might lead to decision-makers only considering a limited set of possibilities which will increase the risk of making sub-optimal decisions (Anderson, 2001)

It is important to recognize that also experienced decision-makers are subject to framing effects (Tversky & Kahneman, 1986). This is consistent with the concepts of bounded rationality (Simon, 1955). Decision-makers can develop skills to reduce framing biases, although this requires accurate assumptions of condition and responses, arguably being hard since financial decisions usually have low causality (Tversky & Kahneman, 1986). For example, the outcome is usually delayed, continuous changes in the external environment can impact the outcome, and lack of information of what outcome alternative decisions would have generated (Tversky & Kahneman, 1986). This, in turn, might explain why it can be problematic to try to solve a financial problem by relying on intuition (Kahneman & Klein, 2009)

2.2 Bias

Biggs, Bedard, Gaber and Linsmeier (1985) concluded that different tasks and similarities in the decision-making process do affect loan officers' capabilities to make decisions. They mention that these sorts of effects tend to occur when a decision-maker calculates the cost and benefits of a potential decision. However, for it to have any practical implications on loan officers' decisions in regard to credit applications, they argue that more research in specific areas needs to be conducted. The findings of Berger and Udell (2002) indicate that loan officers use different ways to process credit applications although following the same credit policies. They state that loan officers collect and use both soft and hard data when assessing credit applications. Here, soft data is characterized as relationship-based data, being hard to quantify and subjective whereas hard data is characterized as financial-based data, being numerical and objective. Furthermore, Berger and Udell (2002) state that organizations that use relationship-based data need to give individual loan officers more authority since they have the best access to soft data and because this data is hard to transfer throughout the organization.

On a similar topic, Maznevski, Kemp, Overstreet and Crook (2001) found that both financial- and relationship-based data had a significant impact on loan officers' decision-making. Even though they found that loan officers relied foremost on financial data whereas relationship-based data was mainly being used when faced with marginal cases, i.e. where the decision to approve or reject the application was not apparent. Furthermore, they stated that marginal cases are the main source of type I and II errors, that is the risk of granting credit to uncreditworthy applicants and the risk of declining credit to creditworthy applicants, respectively and also, that marginal cases becomes increasingly important as competition increases (Mazneski et al. 2001). By basing the credit assessment on subjective relationship-based data, it might increase the risk of making a biased assessment. In this area, Campbell, Loumioti and Wittenberg-Moerman (2019) examined if human biases impact the interpretation of soft data by examining a US credit union and found that credit quality decreased when loan officers issued credit while being overloaded, as well as issuing credit before weekends.

Lipshitz and Shulimovitz (2007) also found that loan officers integrate hard- and soft data when making credit decisions. They concluded that loan officers frequently rely on their gut feeling or intuition based on experience to cope with uncertainty, which has a strong impact on their decisions. Furthermore, they found that loan officers viewed assessments done by using intuition as constituting a more valid indicator than financial data to evaluate creditworthiness (Lipshitz & Shulimovitz, 2007). These findings might be problematic since humans' ability to assess the truthfulness of personal communication is unreliable, thus this might increase the risk of making sub-optimal decisions (Trönnberg & Hemlin, 2012). Contrary to how loan officers process and handle credit assessments today, borrowers do expect that their credit application is handled in a standardized and consistent manner (Wilson, 2016). That loan officers are biased upon making decisions has been illustrated by previous research. For instance, Bacha and Azouzi (2019) conclude that female loan officers are more conservative and risk-averse than male ones. Furthermore, Dobbie, Liberman, Paravisining and Pathania (2021) found significant bias against older and immigrant applicants when examining consumer lending using a UK context but found, in contrast to other research, no bias concerning gender.

Another paper by Busenitz and Barney (1997) explored the behavioral differences in the decision-making processes between entrepreneurs and managers in large organizations based on two types of biases: overconfidence and representativeness. The study was not conducted on an individual basis, but rather on entrepreneurs and managers as groups. The authors concluded that entrepreneurs are more receptive to these types of biases in decision-making processes. This research perspective shows other contexts that fill a specific gap in the ever-expanding research in decision-making connected to bias. Other authors have studied the possibility of improving decision-making by reducing bias using diverse teams with different perspectives (Olson, Paravitam & Bao, 2007). Something that also was explored and tested by Meissner and Wulf (2017) who found different ways of improving the decision-making process in teams to reduce bias by investigating a potential link between cognitive diversity and the delusion of control bias.

2.3 Noise

Previous research has illustrated how human bounded rationality contributes to suboptimal decision-making. For example, when professionals are faced with identical cases they show inconsistency in their decision making, which is referred to as noise (Kahneman et al. 2016). However, some decision-making processes are noise-free, but most are not, which they mean is explained by the level of judgment inherent in the process. To exemplify, when loan officers' are assessing a credit application, they have to make some judgment calls directed by informal experiences. This explains why decision-making often entails some noise. But like previously mentioned, the problem is not the existence of noise, it is rather the level, and when it exceeds a threshold that the organization considers as acceptable (Kahneman et al. 2016)

Deakins and Hussain (1994) found considerable variation between loan officers' decisions when examining credit assessments in the UK. The study concluded that whether entrepreneurs receive funding or not depends largely upon which specific loan officer and branch they apply at, despite that the examined banks used standardized credit assessment guidelines. This might be explained by the found differences between loan officers' assessment of the importance of presented data. Deakins and Hussain (1994) also established that loan officers put too much emphasis on trying to avoid type I errors relative to type II errors. This was explained by loan officers being risk-averse and because type I errors show themselves in terms of credit losses, in contrast to type II errors which are not easily discovered (Deakins & Hussain, 1994).

Bruns, Holland, Shepherd and Wiklund (2008) studied Swedish loan officers' credit assessments from SMEs. The authors found inconsistency between loan officers´ decision-making, contrary to the common belief that loan officers´ who are following the same guidelines make similar decisions. They also found that loan officers were significantly more likely to grant credit to applicants believed to possess similar characteristics as themselves. To explain the findings, Bruns et al. (2008) reason that loan officers collect and assess uncertain information, therefore they must rely on their judgment upon making decisions and since every individual loan officers possess different cognitive capabilities this will lead to inconsistency.

Nilsson and Öhman (2012) interviewed managers and loan officers at one of the major Swedish banks and concluded that ambiguous lending strategies were interpreted differently among loan officers. It stated that this together with factors such as external economic climate and regulation may make loan officers defensive and risk-averse upon assessing loan applications, which can lead to fewer type I errors but increased levels of type II errors. Nilsson and Öhman (2012) argue that this might also be explained by control systems focusing on hard data, which is easier to process and perceived as more factual, which is viewed as important since loan officers are accountable towards the bank and credit committees. This can be related to findings made by Sajasalo, Auvinen, Takala, Järvenpää and Sintonen (2016) who examined a Finnish bank. The scholars found that the organizational strategy was interpreted differently across different levels and among different actors within the bank (Sajasalo et al. 2016).

2.4 Summary & Formulation of Hypotheses

To summarize, there is indisputable importance of understanding human decision-making as it has been proven to be characterized by bounded rationality. This explains the human tendency to show cognitive biases and inconsistency, or noise, upon making decisions. In reviewing previous literature regarding loan officers performing credit assessment, it is made apparent that also this process incorporates bias and noise. This is somewhat contrary to the common belief that credit assessments are performed in a relatively standardized and objective manner, leaving little room for human judgment. However, previous research has not specified how the existence of bias and noise impacts the outcome of made credit assessments.

Previous studies have focused on measuring the impact of bias in terms of whether loan officers accept or reject credit applications. Also, an emphasis has been on bias about discrimination rather than examining how theoretical knowledge of decision-making and bias can be used to enhance credit assessments. We argue that there is a need to specify the level of impact in terms of the amount of credit granted, interest rate given, and perceived risk with the application. Based on this, the following two hypotheses have been constructed.

Hypothesis 1:

Bias affects loan officers decision-making when assessing mortgage credit applications

Hypothesis 2:

Bias affects individual branches decision-making when assessing mortgage credit applications

Previous research has illustrated inconsistency among loan officers when performing credit assessments. Although they have not specified how this inconsistency or *noise* translates into the actual outcome of the process, that is the amount of credit granted, interest rate given and risk perceived with the application. This is believed to be important since the existence of noise, like bias, might lead to suboptimal decision-making. Hence, the following hypotheses will be tested.

Hypothesis 3:

Individual loan officers show differences in noise when assessing mortgage credit applications

Hypothesis 4:

Individual branches show differences in noise when assessing mortgage credit applications

The reasoning for examining the impact of bias and the level of noise among individual loan officers as well as on branch level is that it allows organizations to pinpoint where in the organization bias and noise occurs, and thus, enabling changes to be made if deemed necessary.

3 Methodology

The following chapter provides a thorough review of the chosen methodology. In summary, the present study used a quantitative, deductive, and case study approach to test the four stated hypotheses based on theoretical knowledge regarding noise and bias. Firstly, a description of the research context and the research subject is provided, followed by a description of the research approach and the questionnaire which was used for data collection. After that, the measured variables and samples used in the study are described. Then, a description of how bias and noise were measured and analyzed is presented. Lastly, a discussion and reasoning regarding the validity and reliability of the methodology is presented, together with a discussion of the study boundaries and limitations.

3.1 Research Context

3.1.1 Decision-Making Process

This section explains and argues why the mortgage credit assessment process was chosen as the decision-making process to study the theoretical concepts of bias and noise. Furthermore, it aims to elaborate on the importance of the credit assessment process as a vital function in our society and why studying it can provide interesting practical and theoretical implications.

Purchasing a home is an important transaction for an individual or a household and since most can not finance the purchase with equity they have to finance it by applying for a mortgage. This makes a well-functioning mortgage market crucial for both households and the overall economy. Banks' are the key mortgage suppliers, tasked with performing efficient capital allocation and liquidity creation (Berger et al. 2019). Credit assessments can be argued as constituting banks´ most important decision-making process (Pereira, Ferreira & Chang, 2019). This became apparent during financial crises, nonetheless during the 2007-09 crisis that was partly explained by mispricing of risk within US mortgage debt. To specify, a mortgage is a loan where the lender has a legal claim of the underlying property which is realized if the borrower fails to repay (Berger et al. 2019).

How banks decide whether to accept or reject mortgage applications can be understood twofold, firstly by considering relevant laws and regulations (Haselmann & Wachtel, 2010) and secondly by considering organizations' chosen strategy or credit policies (Win, 2018). From a Swedish context and regulatory point of view, the Swedish Financial Supervisory Authority has in recent years put effort on trying to reduce increased indebtedness in the household sector by implementing different legislations. The latest amortization requirement was implemented in 2018 and states that all newly issued mortgages that exceed 4.5 times the borrower's annual gross income must be amortized by at least 1 percent in addition to existing amortization requirements (Svenska bankföreningen, 2020). Also, according to Swedish law, lenders must base the credit assessment upon the borrower's capacity to repay the credit rather than the value of the underlying collateral (Konsumentkreditlag, 2010).

For lenders, the goal of the credit assessment is to accurately evaluate the creditworthiness of applicants, that is the likelihood of applicants fulfilling the mortgage obligation. This is achieved by loan officers collecting and assessing accounting and non-accounting data in order to reduce information asymmetry, thereafter weighting the estimated creditworthiness against the return of lending to decide whether to approve or reject the application (Andersson, 2001).

The credit assessment process can further be understood by imagining a spectrum with opposite poles named transactional- and relationship-based lending. Transactional-based lending consists of assessing creditworthiness by focusing on “hard data", being quantitative and objective, such as debt-to-income ratios and credit scores. In contrast to relationship-based lending which also considers "soft data", that is more qualitative and subjective, involving, for example, assessment of an applicant's character or sincerity (Berger & Black, 2011). Although the primary focus is on assessing applicants' repayment capacity, much emphasis is given to hard data such as applicants’ income and wealth (Swedish FSA, 2020). To evaluate the repayment capacity, banks do a discretionary income calculation. In short, this means that the loan officer plugs in data regarding the applicant’s income and debt, then deducts estimated costs, such as running costs, tax, interest, and amortization, which generates a surplus or a deficit (Swedish FSA, 2020). The deficits generally lead to a rejected application (Swedish FSA, 2020).

3.1.2 Research Subject

To understand and analyze decision-making related to credit assessments one must consider the institutional environment in which the process takes place (Win, 2018). Thus, this section aims to identify the institutional environment of the chosen research subject, Handelsbanken (SHB), and the factors which drive and control their decisions related to mortgage credit assessments. Also, the section aims to explain why SHB was chosen as a research subject.

SHB´s annual report provides valuable information to understand its credit assessment process. It states that SHB´s strategy rests heavily on decentralization, meaning that individual branches have extensive credit responsibility and mandate when making credit decisions (Handelsbanken, 2020). This corresponds with SHB describing themselves as being a relationship bank, where the local presence and establishing in-depth relationships with customers are viewed as important to ensure high credit quality (Handelsbanken, 2020). This is further embraced by a culture that emphasizes low-risk tolerance and a belief in individual employees´ decision-making ability (Handelsbanken, 2020).

The focus on low-risk tolerance is translated into goals of achieving low-credit losses regardless of the currently existing state of the macro-economic environment. This is achieved by focusing on customers with strong repayment capacity and financial positions, described by SHB as: “being selective in its choice of customers" (Handelsbanken, 2020, p 106). Furthermore, that weak repayment capacity can never be justified by referring to higher volumes, margins, or satisfactory collateral (Handelsbanken, 2020). The concept has historically been proven successful since SHB has generated profitability, customer satisfaction, cost-effectiveness, and credit quality above peer banks’ average (Handelsbanken, 2020). It was named the world's safest bank by Global Finance and received the world’s highest credit ratings by Fitch, Moody's, and Standard & Poor's (Handelsbanken, 2020).

SHB has been examined through the lens of their employees - from their perceptions - which overall, corresponds to and thus validates descriptions found within the annual report (Cäker & Siverbo, 2014). Previous research describes that the bank's decentralized model was first implemented in the 1970s when Jan Wallander was hired as CEO which led to a radical change of SHB´s management policies. This led to credit policies switching focus towards ensuring that every individual customer had high credit quality, in contrast to using a portfolio-based approach (Lindsay & Libby, 2007). To achieve this, it was believed necessary to increasingly move decision-making authority to branch managers, since individual branches were viewed best suited to make operational decisions, i.e. credit decisions (Lindsay & Libby, 2007).

Previous research from Cäker and Siverbo (2014) has illustrated how SHB uses socio-ideological controls to anchor customer focus, cost-efficiency, and prudence within the organization to empower employees and increase strategic alignment. The achievement of empowerment is apparent since employees view their branch as the bank, whereas the rest of the organization as support functions. Examples of socio-ideological controls used within the bank include new employees receiving and discussing the book “our way” which describes Jan Wallander’s philosophies how the bank should be run, and further, by a 98 percent high level of internal recruitment to management positions (Cäker & Siverbo, 2014; Handelsbanken, 2020). Also, they monitor strategic alignment by using different control measures, aligned with mentioned core philosophies, for example, continuous meetings between branch- and area managers discussing key performance metrics (Cäker & Siverbo, 2014). Another control measure is that employees follow a standardized credit approval process, leading to less subjectivity embedded within the process, such as more focus on the longevity of applicants’ income, rather than specific occupation (Cäker & Siverbo, 2014).

In summary, since SHB’s strategy consists of using a highly decentralized business model and relationship-based lending, it was believed to provide an interesting context and explain why SHB was chosen as a research subject. The reasoning was that the strategy might cause levels of bias and noise among loan officers and on a branch level that differ from what the organization as a whole deems optimal. Also, when SHB´s mortgage portfolio was put in relation to profits, the process was argued as being their most important decision-making process (Handelsbanken, 2020). SHB is also important for the wider economy considering that SHB is the second-largest market actor within the Swedish mortgage market, with outstanding mortgage debt, amounting to 851 billion SEK in 2020. Altogether, this provides the reasons as to why SHB was chosen as a research subject.

3.2 Research Approach

3.2.1 Deductive

The numerical data for the study was collected from a questionnaire that laid the foundation for this quantitative study, aimed at assessing the relationship between data, theory, and results. The study is therefore deductive in nature, collecting and analyzing empirical data within a theoretical framework to assess the feasibility of specific hypotheses (Bryman & Bell, 2017). The study considered four hypotheses formulated using the theory around bias and noise described in the literature review, see Chapter 2. The four hypotheses were tested against collected data from the questionnaire, being either rejected or accepted. The deductive process is according to Merton (1967) fitting for sociological studies which considers the behavior of groups or institutions.

3.2.2 Quantitative Research

According to Bryman and Bell (2017), most research applies either a quantitative or qualitative approach. The quantitative approach evaluates empirical data through a theoretical framework, commonly applying a deductive approach to establish the relationship between theory and reality. Through a quantitative approach, the process of collecting and evaluating data may describe structural behavior within or between groups (Bryman & Bell, 2017), which is why the study applied a quantitative rather than a qualitative approach.

An added benefit of the quantitative research approach is the collection of quantitative data, which, according to Yin (2018) can be considered a far more robust methodology than a narrative or non-numerically approach common in qualitative research. An interview-oriented qualitative method also allows for the interviewer to subconsciously impact the interviewee due to the social context of the interview and the formulations of the questions. Bryman and Bell (2017) do, however, mention the limits of a quantitative approach when deciphering human behavior since the complexity of human behavioral psychology is not easily quantified and follows far more capricious patterns.

3.3 Research Questionnaire

To discern the degree of bias and noise between individuals and branches within a specific business, loan officers from three different branches answered a questionnaire. The questionnaire was centered around four separate cases where each branch's loan officers individually answered three questions for each case. These questions were: the amount of credit granted, interest rate given, and the perceived risk with each case. These variables were chosen on the basis that they were treated as the most important factors in the decision that loan officers need to take into consideration, both from the standpoint of the borrower and the lender. Each of the four cases consisted of a standardized fictional mortgage credit application from couples inquiring about a credit and interest rate estimate. The name, age, occupation, and the salary was provided for each individual in the couple. All couples were ascertained to be without debt or debt defaults. They did also have similar first- and surnames derived from the same geographical region. See Figure 2 for an example of one of the applications that were used. The research questionnaire in full is appended in Appendix A.

Ansökan I

	Sökande 1	Sökande 2
Namn	Love Eckhart	Elsa Simonsson
Ålder	39	35
Yrke	Svetsare	Vårdbiträde
Månadsinkomst (före skatt)	44 000	36 000

Beviljat lån: ____________ till ränta ______ % 3-mån rörlig

Risk: Väldigt Låg ○ Låg ○ Medel ○ Hög ○ Väldigt Hög ○

Figure 2: Illustration of one of four fictional mortgage credit applications, please note that the application is in Swedish.

To be able to assess bias in terms of occupation and age, the four separate cases from the questionnaire were structured as two pairs of comparative cases. For the first case pair (case 1 and 4) the applicants were separated solely in terms of occupation. One of the pairs had occupations socially regarded as more prestigious, while the second pair had occupations regarded as less socially prestigious. The applicants in case 4 were a lawyer and a psychologist, while the two applicants in case 1 were a welder and a care assistant. To decide what constitutes a “high” or “low” prestige occupation, we refer to a sociology report by Svensson and Ulfsdotter (2019). In the second pair of cases (Case 2 and 3) the applicants were separated solely in terms of age, where one case had applicants far younger than that of the comparative case. In Case 2 both applicants were in their young twenties, while the applicants in Case 3 were in their mid-fifties, see Appendix A. Each loan officer assessed the maximum possible credit granted to each pair, along with the 3-month variable interest rate and a risk assessment from “very low” to “very high” using a Likert scale.

3.4 Data Collection

3.4.1 Sample & Variables

To find respondents to participate in the study, 3 branch managers at SHB were inquired through email. Due to Covid-19, data was collected online, where participants received a link to the questionnaire through us from their respective branch managers. A total number of 15 loan officers participated in the study with 5 loan officers from each branch, see Table 1. The answers were collected anonymously from the loan officers and without specifying the branches that participated in the study. All the branches were located within the same city and also, within a similar proximity area. The study aimed to discern the impact of bias due to variation within the two variables *occupation* and *age*, as well as discern the level of noise among loan officers and between branches. Three variables were considered: credit amount, interest rate, and perceived risk. Since the statistical difference among loan officers and within branches was determined through an *unpaired t-test*, a large number of participants was preferred as it increases the credibility and validity of the study. A sample population of 30 or more would have been ideal, but not necessarily according to Körner and Wahlgren (2015). Yet, the number of loan officers that worked at one specific SHB branch usually did not surpass 10 or more individuals, as partly illustrated by Table 1. The sample consisted of loan officers whose day-to-day practice included the assessment of mortgage applications, with experience ranging from 0 to 37 years, where the average was 11 years. The data was evaluated using Matlab, Python, and Excel.

Branch	1	2	3
Number of loan officers' answering the questionnaire	5	5	5
Number of loan officers working at the branch	5	11	5
Participation rate	100 %	45 %	100 %

Table 1: Illustration of number of respondents answering the questionnaire, number of loan officers working at each branch, and participation rate.

3.4.2 Alternative Sources of Data Collection

Collecting data to assess bias and noise could also have been done through a personal interview, instead of a questionnaire. Yet, Bryman and Bell (2017) alluded to specific problems implicated with using interviews to collect data. The interviewer or the social context could have impacted the interviewee, possibly resulting in skewed or non-representative results. In measuring bias and noise it is of utmost importance that we controlled the different variables that could have impacted the result in a standardized format. Thus, using a standardized case approach generated the control of the variables which was deemed necessary to measure the impact of bias and the level of noise.

3.5 Measuring Bias

3.5.1 Unpaired t-test

Bias is considered systematic differences in answers. If a group or individual is biased, the resulting answer would be systematically skewed in one direction. For instance, if a group of loan officers was positively biased towards tall applicants, they would have continually and systematically been giving tall applicants lower interest rates than short applicants.

Bias was evaluated through statistical hypothesis testing, comparing the difference between two independent population means. Because the total amount of participants was less than thirty, bias was deciphered through an unpaired t-test:

$$t = \frac{(\bar{X}_1 - \bar{X}_2) - d_0}{\sqrt{s^2_p(\frac{1}{n_1} + \frac{1}{n_2})}} \quad where: s^2_p = \frac{(n_1 - 1)s^2_1 + (n_2 - 1)s^2_2}{n_1 + n_2 - 2}$$

$\bar{X}_1$ and $\bar{X}_2$ denotes the mean assessment for branch 1 and 2 respectively, while n_1 and n_2 denote the sample size, and s_1 and s_2 denote the standard deviation, and d_o is set to zero.

The null hypothesis (H_0) considered there to be no difference due to bias between two independent population means, while the alternative hypothesis (H_1) indicated difference due to bias, formulated as:

$$H_0: u_1 - u_2 = 0$$

$$H_1: u_1 \neq u_2$$

Where u_1 is the mean from the first population mean and u_2 is the second population mean. The null hypothesis assumed variation between the applications to be due to random distribution within samples n_1 and n_2. The null hypothesis is accepted unless the unpaired t-test indicates, with 5 percentage significance, that the difference is not due to random distribution, and the alternative hypothesis is accepted.

3.5.2 Bias Amongst Individuals

The questionnaire consisted of four separate cases, see Appendix A, where each case consists of a fictional mortgage application. The four cases in the questionnaire are divided into two separate case pairs, pair one being case 1 and 4, while pair two being case 2 and 3. This division into case pairs was not made aware to the participants, since each case pair aims at assessing potential bias. Each pair is centered around a specific variable (*age* or *occupation*). For the pair aimed at evaluating bias due to the variable *occupation*, the applicant's age is similar and the total income is equivalent for both applications, see cases 1 and 4 in Appendix A. For the case pair aimed at evaluating bias due to the variable *age* the occupations are similar, i.e considered socially neither a “high” or “low” prestige occupations, and the total income is equivalent for both applications, see cases 2 and 3 in Appendix A. It was also important that income for all individuals were within the same tax bracket since income is denoted as gross salary.

We reasoned that applicants who differ solely in terms of having an occupation considered socially more prestigious, or being older, should not have received better credit conditions. If two applicants are equivalent in all aspects except for one variable, the resulting credit assessment by individual loan officers should have been equivalent if the variable in question should not have impacted the assessment. To determine whether bias existed between individuals, all participants from the three branches were grouped together, where we used a t-test to determine bias between cases within a case pair. A total of 15 loan officers participated in the study, resulting in 14 degrees of freedom and a critical t-value of 1.761, see Appendix D.

3.5.3 Bias Within Branches

Bias due to either the variable *age* or *occupation* has also been tested on a branch level using an unpaired t-test. The t-test was performed between cases within a case pair for all three branches separately. Since each branch consisted of five loan officers, resulting in four degrees of freedom, a critical t-value of 2.132 was applied, see Appendix D for the t-table with critical values.

The feasibility of using a t-test and statistical significance to indicate bias was discussed in relation to the small sample size. As previously mentioned, the number of loan officers working at each branch did not exceed five individuals for two out of three branches. The low number of individuals in each population when calculating bias resulted in the assessment of each individual heavily impacting the results of the t-test. Yet, the t-test employs the premise of degrees of freedom, where a smaller population resulted in lower degrees of freedom and an increased critical t-value, making it more difficult to prove a statistical significance. It should also be mentioned that the evaluated t-test was heavily impacted by the standard deviation within each group as well as the mean difference in assessment. The large difference in mean value along with a relatively small standard deviation within each group resulted in a higher t-value. Therefore two branches did exhibit the same mean difference between two cases, yet only one branch showed a statistically significant mean difference since the standard deviation was lower for that specific group.

A secondary problem connected to the low sample size is the potential of a standardized answering process resulting in multiple loan officers' giving the exact same answer to a specific question. If all officers within a sample gave the same answer the resulting standard deviation becomes zero and, since the standard deviation is in the denominator, the t-value becomes unreasonably high. This might have created a problem when evaluating bias through a t-test using a small sample size likely to give standardized answers.

3.6 Measuring Noise

To measure noise which is the level of variation among answers, the relative approximation error was used to perform the statistical analysis. Noise does not indicate whether an answer is right or wrong, only the variance amongst them and is, therefore, a relative term, only descriptive as it relates to something else. Noise could therefore be described as the error amongst answers. If A is noisier than B the error is larger amongst the answers for A than B.

To evaluate noise the *relative approximation error* is used, defined as:

$$Relative\ approximation\ error\ = \frac{|\bar{x} - x_i|}{\bar{x}}$$

Where $\bar{x}$ is the mean and x_i is the individual assessment of a loan officer. The relative approximation error was calculated in terms of credit granted, interest rate, and perceived risk individually for all four cases, see Appendix A for the research questionnaire.

The relative approximation error was calculated for each loan officer within a group, which resulted in an error distribution between the individual with the largest and lowest relative approximation error. The result was a range or interval of errors within a group when a specific case was assessed. A range or interval indicated that the error distribution within a group was, in this study, considered to be a better indicator of noise than an individual number, such as the *standard error*.

Since risk was assessed through the Likert scale, which is an ordinal scale according to Bryman and Bell (2017) ("Very Low" to "Very High"), each assessment was weighted in accordance with Table 2. This allowed for each level of risk to correspond with a specific quantitative value, which was used to determine the relative approximation error in terms of risk for each branch. As each assessment on the scale is weighted using natural numbers (whole numbers) between one and five, and not a ratio scale, the difference in risk assessment between loan officers will be exacerbated. Risk is also a subjective assessment, what is considered "moderate" risk for one loan officer may be considered "Very High" risk for a more risk-averse loan officer. Therefore, it was discussed whether risk, being such a subjective assessment, is a valid metric when dealing with bias or noise.

Risk	**Weight**
Very Low	1
Low	2
Moderate	3
High	4
Very High	5

Table 2: The corresponding weight associated with each level of risk on the Lickert scale.

To decipher the impact of noise the study considered the premise of "variability across individuals" described by Kahneman et al. (2016) as professionals in the same role making different decisions when faced with identical problems. Naturally, individual loan officers' assessments vary, as individual decision-making is limited by bounded rationality. If professionals in the same business were supposed to make similar assessments, the variance in the amount of credit granted, interest rate, and perceived risk should vary to the same degree amongst loan officers. Therefore, certain levels of variance between different loan officers' credit, interest, and risk assessments were expected, and the existence of variance in itself was not considered to be problematic. This is also made evident since no single right decision exists for the presented problem. Therefore, in a practical sense, what was considered noisy is usually up to the individual organization to decide. This was also largely dependent upon the specific context, meaning that a 10 percent level of noise might be considered unacceptable when making a diagnosis of cancer, whereas acceptable when deciding the amount of credit that should be granted.

A benefit of the relative approximation error is that a percentage error is a simple and commonly used term. The relative approximation error is also normalized, i.e. it describes the relative relation between the mean and an individual loan officer's assessment in percentage. As the relative approximation error was dimensionless, being only a relationship between two values, the noise or error amongst officers is comparable between variables. This meant that the error amongst officers when assessing credit could be compared to the error when assessing interest. If instead noise was denoted as the standard deviation, noise when assessing credit would be described in terms of SEK while noise when assessing interest would be described in terms of percent, allowing for no comparison between the two variables.

3.7 Validity and Reliability

According to Bryman and Bell (2017) replicability (i.e. the possibility of replicating the same results using the same methodology) is a common criterion for most business organizational studies. Therefore, all details concerning the methodology as well as the questionnaire have been provided in the various appendixes. Although the study could be replicated fully, the results may vary as the degree of noise and bias between individuals or branches depends on human factors as well as sampling.

Yin (2018) considered four criteria essential for assessing the validity of any case study, one of them being replicability. *Construct validity* is centered around how well the operational measures match the concept of the study, *internal validity* considers the feasibility of the correlation between the phenomena and the describing variable, i.e. the degree to which a function's behavior is described by the underlying variables. The last form of validity mentioned by Yin

(2018) considers the applicability of the result in a broader context or other adjacent fields denoted as *External validity*.

The ambition was to create a formal and serious questionnaire since this was believed to increase both the validity and reliability of the result. The questionnaire's format was based on information from real credit applications from SHB:s website and validated by several branch managers within SHB. After feedback was received, the questionnaire was slightly adjusted to align with the advice received from the branch managers before it was distributed and tested. To further increase the validity of the questionnaire, it was tested by a small group of loan officers to ensure that the questions and format were understood.

According to Hair, Black, Babin and Andersson (2019) to ensure the validity of the study, the variables that were chosen must correctly represent the concept of the study, which Yin (2018) refers to as construct validity. To discern potential bias surrounding a particular variable, the decisions needed not to be affected by variation in other variables. Therefore, the cases in the case pairs were identical to one another except in one aspect, namely the variable *occupation* for applications 1 and 4 or the variable *age* for applications 2 and 3. Furthermore, all the branches were located within the same city, therefore there were no geographical differences that impacted the result. Something that hopefully increased the internal validity of the study, resulting in fewer variables that impacted the result.

3.8 Study Boundaries & Limitations

Although the present study was limited to Handelsbanken and the credit assessment process, the methodological framework was not. The underlying foundations of the framework used a standardized questionnaire that could have been adjusted to fit any other organization or decision-making process.

Further, it should be noted that the results derived from the present study do not necessarily provide an exact representation of the results that would have been derived by using a larger sample size. It was deemed reasonable to assume that other results in numerical terms would have been derived by using another sample or sample size. However, at the same time, the derived conclusions regarding the existence of noise and bias were reasonably assumed to be similar, or the same that would have been derived by using another sample or sample size. As the used sample in the present study is assumed to have had similar or the same characteristics as other samples in the population. In other words, the chosen sample size of loan officers within Handelsbanken was not deemed to be unique when compared with other loan officers within the bank.

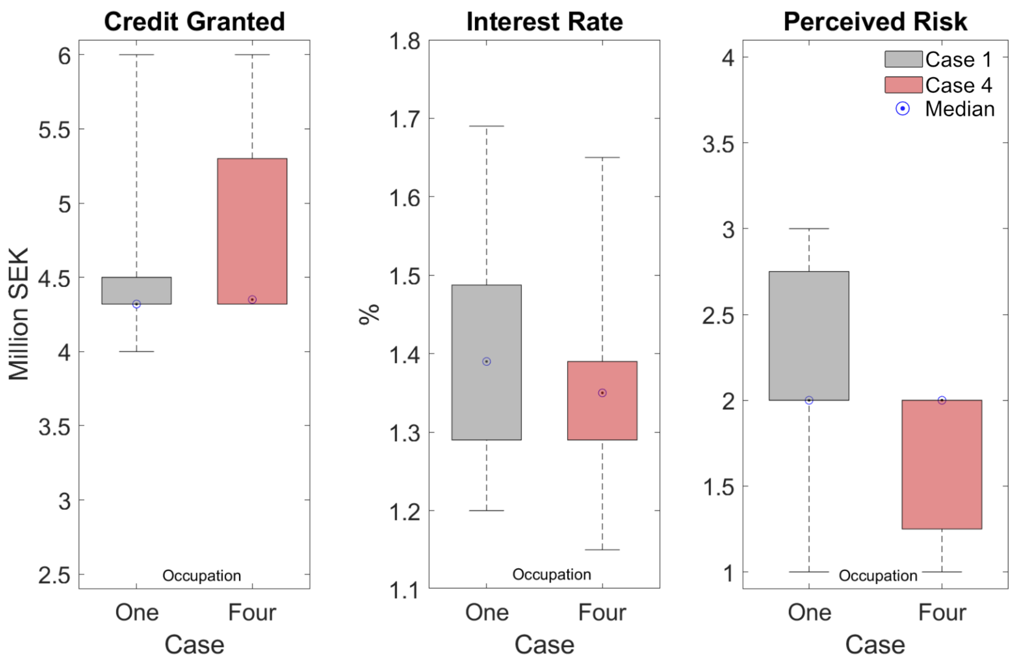
A limitation of the present study is that it does not capture the underlying reasoning that controls how individual loan officers reached their decisions, in other words, what cognitive processes that could possibly have explained the existence of bias and noise. As previously mentioned, when this attempt was made to try to understand decision-making processes it was deemed important to focus on the underlying cognitive processes which control the decisions that were made. This was challenging since the process involved individual judgment which often was made unconsciously. Hence, this was deemed to be outside the scope of the present study.

4 Results

The following chapter presents the results of the present study in the following order: First, the results regarding the effect of bias are presented, both amongst individual loan officers and then within branches. Secondly, the results regarding the level of noise are conferred, first amongst individual loan officers and then within branches.

4.1 Bias

4.1.1 Amongst Individuals

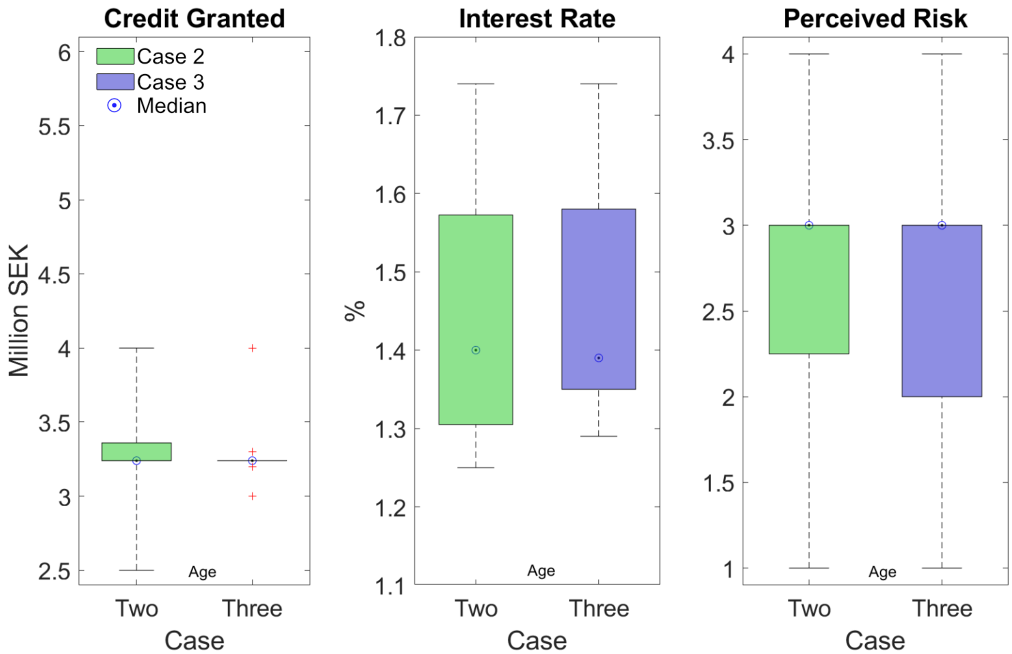


		Credit Granted [10^6 Mkr]	Interest Rate [%]	Perceived Risk [-]
Average	Case 1	4.59	1.40	2.13
	Case 4	4.77	1.35	1.73
	Difference	0.18	-0.05	-0.4

Figure 3: Boxplot and table displaying the distribution of answers for all loan officers assessing cases 1 and 4, concerned with bias due to *occupation*.

In Figure 3 the distribution of answers for all loan officers' within the three branches is displayed through a table and boxplots. The first case pair is concerned with bias due to *occupation,* that is, case 1 and case 4. In case 1 the first applicant is a welder and the second applicant is a care assistant. In case 4 the first applicant is a lawyer and the second applicant a psychologist, see Appendix A for the questionnaire.

Upon assessing all the answers from the loan officers' in Figure 3, the applicants in case 4 received on average 180 000 SEK more in credit, 0.05 % lower interest rate, and 0.4 points lower in perceived risk than case 1. Furthermore, it can be noted that there are differences in the minimum value and the maximum value concerning the three different aspects. For example, by examining the boxplot concerned with credit granted, the minimum value for case 1 is four million whereas the maximum value is 6 million. Quite similarly in case 4, the minimum value is 4.32 million and the maximum is 6 million. For more detailed information about the cases see Appendix B.

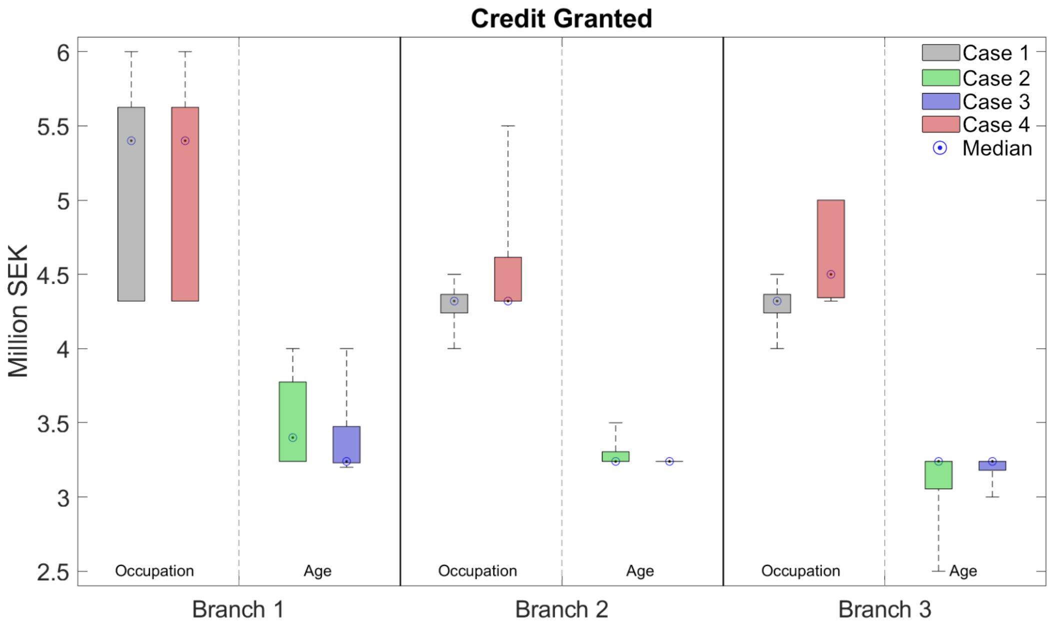


		Credit Granted [10^6 Mkr]	Interest Rate [%]	Perceived Risk [-]
Average	Case 2	3.30	1.45	2.73
	Case 3	3.28	1.45	2.67
	Difference	-0.02	0	-0.07

Figure 4: Boxplot and table displaying the distribution of answers for all loan officers assessing cases 2 and 3, concerned with bias due to *age*.

Figure 4 displays the distribution of answers for all loan officers for the case pair concerned with bias due to *age,* that is cases 2 and 3. The applicants in case 2 are far younger than the applicants in case 3, see Appendix A for the questionnaire. The difference in assessment between case 2 and case 3 is minimal when looking at the average values in the table in Figure 4. The younger applicants in case 2 receive a marginally higher credit amount but are perceived as slightly riskier. As in cases 1 and 4, it is also worth noting the differences in the minimum and the maximum value regarding all three factors. To exemplify, by looking at case 2 in the boxplot and in regards to interest rate, the lowest value is 1.25 whereas the highest is 1.75. For more detailed information about the cases see Appendix B.

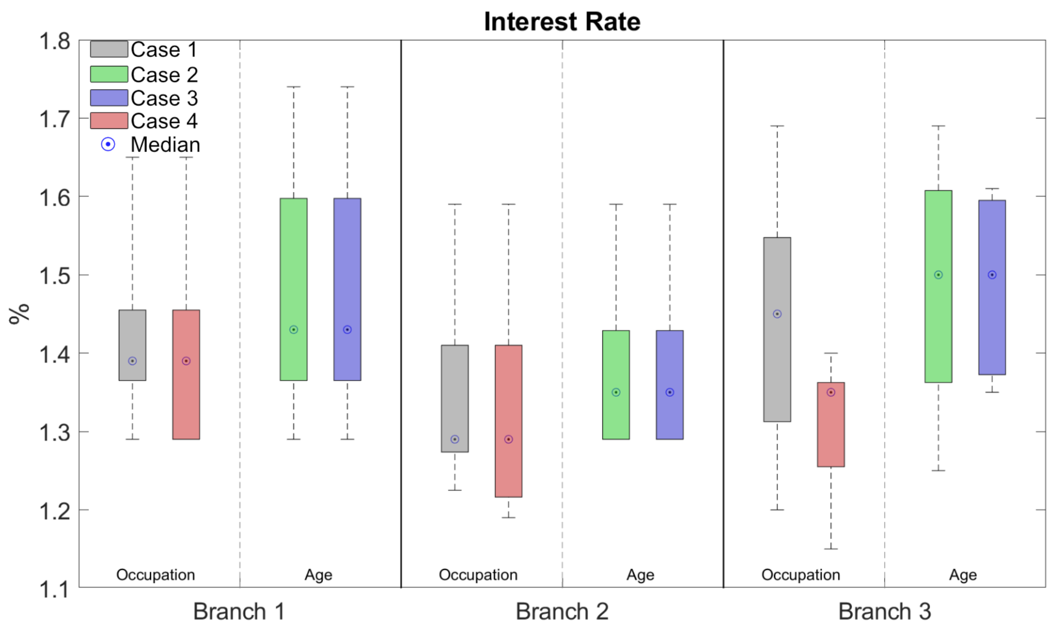
4.1.2 Within Branches



		Credit Granted [M SEK]			
		Branch 1	Branch 2	Branch 3	Description
Average	Case 1	5.11	4.29	4.29	Less-prestigious occupation
	Case 4	5.11	4.56	4.63	Prestigious occupation
	Difference	0	0.33	0.34	
Average	Case 2	3.52	3.29	3.09	Younger
	Case 3	3.40	3.24	3.19	Older
	Difference	-0.12	-0.05	0.10	

Figure 5: Boxplot and table displaying the distribution of answers in terms of credit granted for individual branches.

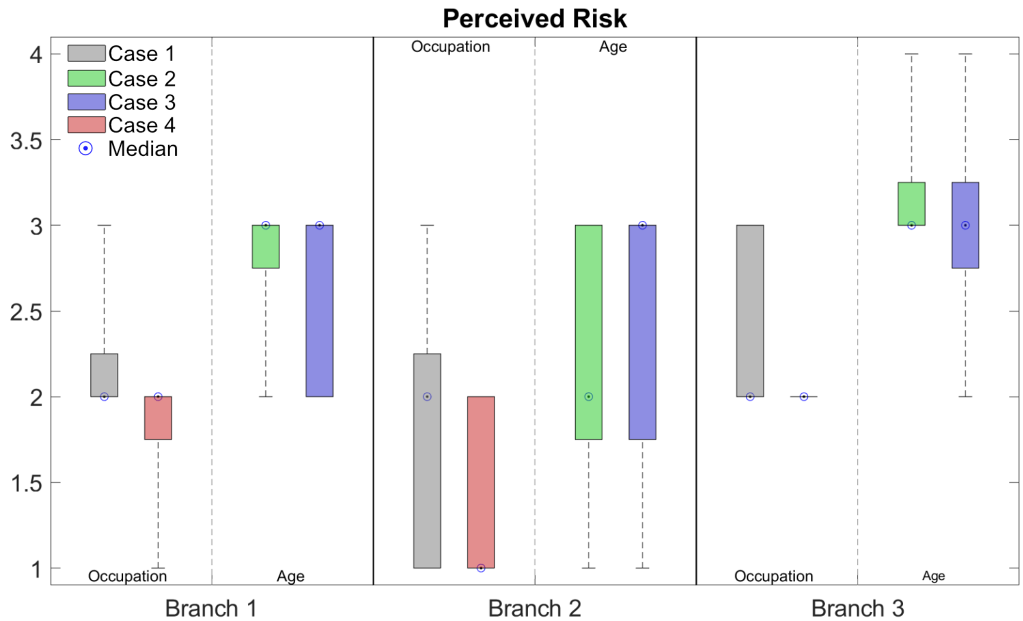
Figure 5 illustrates the distribution of answers for loan officers between the three branches in terms of credit granted. The figure indicates small differences in credit granted when assessing the case pair concerned with the variable *age* which is cases 2 and 3. The case pair concerned with bias due to the variable *occupation* (case 1 and 4) shows noticeable differences for branches 2 and 3. Branch 3 grants higher credit to the applicants with socially considered prestigious occupations, by granting on average 340 000 SEK more compared with those with low prestige occupations.



		Interest Rate [%]			
		Branch 1	Branch 2	Branch 3	Description
Average	Case 1	1.42	1.35	1.44	Less-prestigious occupation
	Case 4	1.40	1.33	1.31	Prestigious occupation
	Difference	-0.02	-0.02	-0.13	
Average	Case 2	1.48	1.38	1.48	Younger
	Case 3	1.48	1.38	1.49	Older
	Difference	0	0	0.01	

Figure 6: Boxplot and table displaying the distribution of answers in terms of the interest rate for individual branches.

The distribution in Figure 6 indicates minor differences in terms of interest rate given to applicants in the case pair concerned with the variable *age* (Case 2 and 3). However, similar to all branches, the applicants with socially more prestigious occupations, in the case pair concerned with bias due to the variable *occupation,* are on average granted a lower interest rate than those with less prestigious occupations. The loan officers' in Branch 3 offered on average a 0.13 % lower interest rate to the applicants in Case 1 compared to the applicants in Case 4.



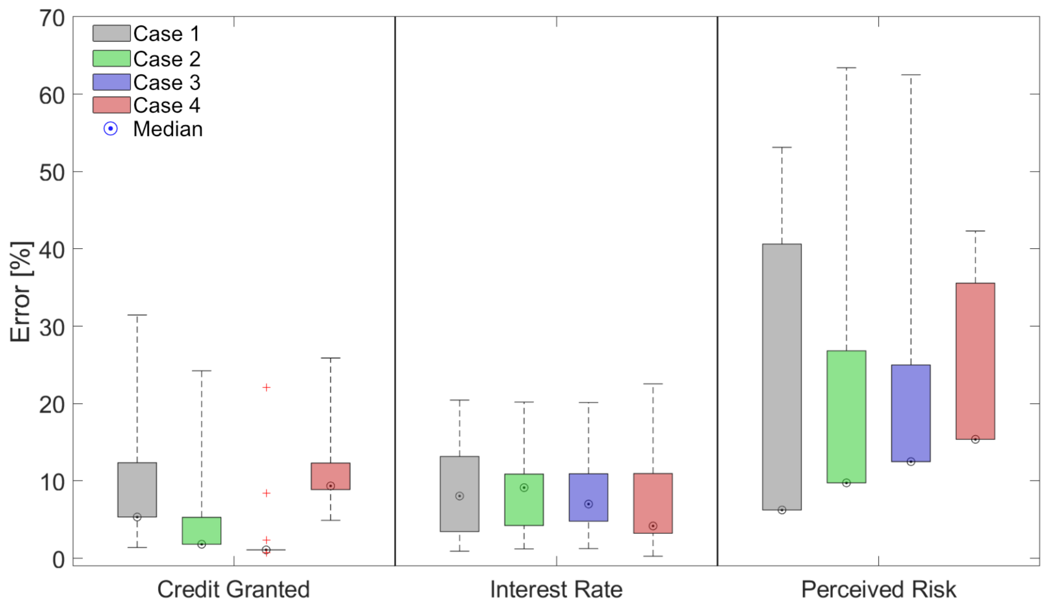
		Perceived Risk [-]			
		Branch 1	Branch 2	Branch 3	Description
Average	Case 1	2.2	1.8	2.4	Less-prestigious occupation
	Case 4	1.8	1.4	2	Prestigious occupation
	Difference	-0.4	-0.4	-0.4	
Average	Case 2	2.8	2.2	3.2	Younger
	Case 3	2.6	2.4	3	Older
	Difference	-0.2	0.2	-0.2	

Figure 7: Boxplot and table displaying the distribution of answers in terms of perceived risk for individual branches.

The distribution in Figure 7 indicates that applicants with prestigious occupations are perceived on average as less risky than their counterparts. On a five-point scale, with values between 1-5, the applicants with the prestigious occupations are perceived as 0.4 points less risky than their less prestigious counterparts for all branches. Older applicants were perceived as 0.2 points less risky than their younger counterparts. For more detailed information surrounding the answers from different branches see Appendix B.

4.2 Noise

4.2.1 Amongst Individuals

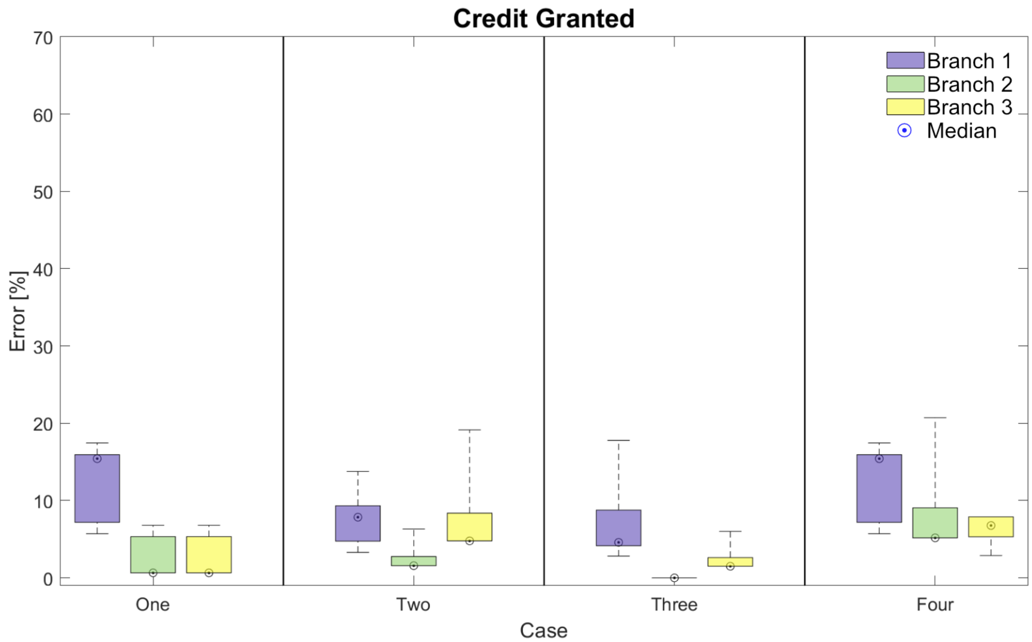


	Error [%]	Case 1	Case 2	Case 3	Case 4
Average	Credit Granted	9.37	5.66	3.14	10.64
	Interest Rate	8.22	8.88	8.19	6.93
	Perceived Risk	21.67	19.19	21.67	22.56

Figure 8: Boxplot displaying the distribution of error (*relative approximation error*) among answers for all loan officers'. Divided according to credit granted, interest rate, and perceived risk for all cases.

Figure 8 illustrates the level of noise among the answers for all loan officers and all variables. Noise is described as the distribution of relative approximation error amongst all individuals divided according to case and variable. The table in Figure 8 indicates a far larger error among loan officers when assessing risk than when assessing interest or credit. This is true in terms of both average error for all cases and error distribution span.

4.2.2 Between Branches

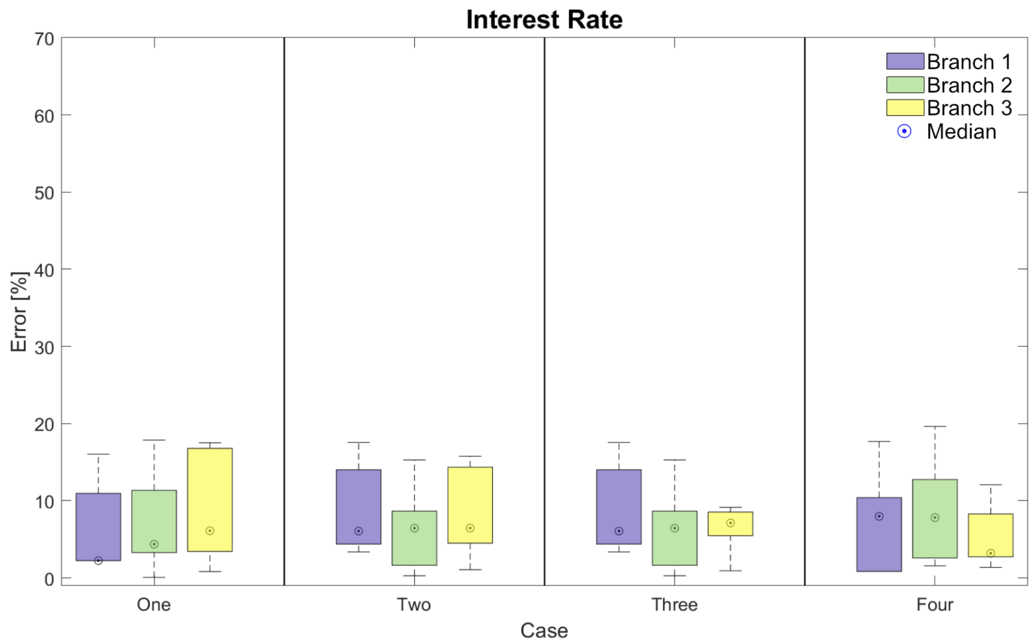


Credit Granted

Error [%]		Case 1	Case 2	Case 3	Case 4
Average	Branch 1	12.34	7.6	7.11	12.34
	Branch 2	2.72	2.53	0	8.29
	Branch 3	2.72	7.66	2.41	6.32

Figure 9: Boxplot and table displaying the distribution error (*relative approximation error*) among answers in terms of credit granted for individual branches. The error in the graph considers the relative approximation error as described in Section 3.6.

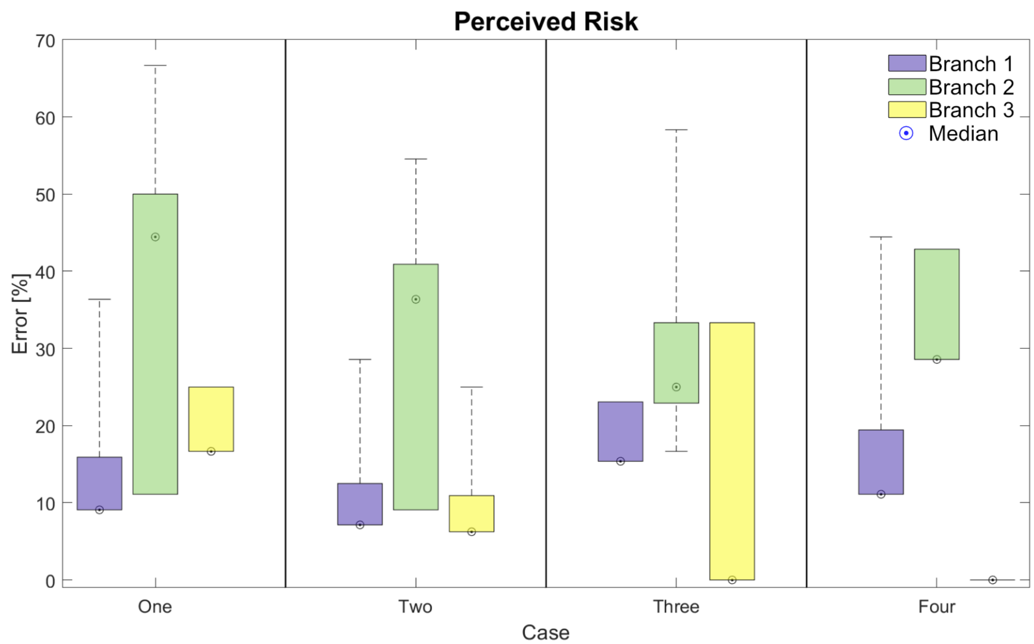
The relative approximation error distribution, or noise, among loan officers' when assessing credit for each case is displayed in Figure 9, divided according to each branch. The table in the figure shows palpable differences in terms of average error between the three separate branches, with branch 1 exhibiting a higher average error for three out of four cases. It should also be noted that the median error is higher for branch 1 when assessing credit for all cases. More details regarding error for the three branches when assessing credit for each case is appended in Appendix C.



		Interest Rate			
Error [%]		Case 1	Case 2	Case 3	Case 4
Average	Branch 1	6.41	8.92	8.92	7.08
	Branch 2	7.18	6.12	6.12	8.49
	Branch 3	9.07	8.57	6.51	5.38

Figure 10: Boxplot and table displaying the distribution of error (*relative approximation error*) among answers in terms of the interest rate for individual branches.

The distribution in terms of error, or noise, when assessing the interest rate for the four cases shows small variation for all branches, see Figure 10. The distribution of error amongst cases and branches is confined between 0 and 10 percent, indicating little variation between answers. This becomes apparent when viewing the table in Figure 10 which indicates that the average error for a single branch never exceeded 10 %.



Perceived Risk

Error [%]		Case 1	Case 2	Case 3	Case 4
Average	Branch 1	14.55	11.43	18.46	17.78
	Branch 2	35.56	29.08	30.00	34.29
	Branch 3	20	10	13.33	0

Figure 11: Boxplot and table displaying the distribution of error (*relative approximation error*) among answers in terms of perceived risk for individual branches.

The perceived risk is assessed through a Likert scale between “Very Low” and “Very High”, with each answer being weighted between one and five, see Table 2 in Section 3.6. The distribution of the relative approximation error displayed in Figure 11 indicates a far larger percentage error when assessing risk than capital or interest. The median risk and average risk are larger for branch 2 than any other branch for all cases. Insinuating a wider distribution of answers among branch 2 than 1 or 3. It should also be noted that there is no distribution of error among answers for case 4 for branch 3 since all gave the same risk assessment. Further details concerning errors among answers are provided in Appendix C.

5 Analysis

This chapter presents the performed statistical analysis. In the first section, the analysis regarding bias concerning individuals and branches is conducted. In the second section, the analysis measuring noise amongst individuals and within branches is conferred.

5.1 Bias

5.1.1 Amongst Individuals

		t-test	
		Casepair 1 [Occupation]	Casepair 2 [Age]
All	Credit Granted	0.949	0.246
	Interest Rate	1.101	0.012
	Perceived Risk	1.969	0.256

Table 3: T-test between application pairs for all 15 loan officers, with a critical t-value of 1.761, see Appendix D.

Based on the t-test analysis above in Table 3, it can be stated that there is statistical significance in the variable perceived risk concerning case pair 1 with a t-value of 1.969 since the critical t-value for a one-sided 95% confidence t-test at 14 degrees of freedom is 1.761, see Appendix D for the t-table. However, the same can not be stated for the rest of the categories concerning case pair 1. Though it is interesting to note, there are higher values in general when examining case pair 1 compared to case pair 2. This leads us to believe that the variable *occupation* has a larger impact on loan officers' decision-making capabilities relative to the variable *age* and is perhaps taken more into consideration. As the t-test displays differences between means, the difference between the assessments in case pair 1 does indicate that the mean difference when assessing cases with variation in *occupation* is larger than variation in *age*, although not statistically significant for the variables credit granted and interest rate. It indicates, similar to previous research findings, that loan officers' judgment impacts the outcome of credit assessments. This can be problematic considering the inherent difficulty of making subjective judgments and valuing soft data.

One can also note that many of the answers concerning credit granted centered around numerical values that are similar or equal to 4,5 times applicants' annual gross income. This is the same cut-off point that, if surpassed, Swedish legislation states that borrowers need to increase their amortization by 1 percent while issuing new mortgage debt. Thus, it seems reasonable to assume that loan officers use this threshold as an anchoring heuristic to help them distinguish from what is a reasonable amount to approve from what is more questionable.

Upon analyzing case pair 2's impact concerning bias for variable *age,* the statistical analysis showed a non-significant impact on loan officers' assessments. The statistical analysis illustrates the minimal difference between loan officers' answers when comparing cases 2 and 3. This indicates that it is unlikely that an applicant's age has an impact on the loan officers' credit assessment and subsequently does not impact their decisions regarding the amount of credit to grant, the interest rate to give or assess the risk inherent in the application.

Altogether, the statistical analysis indicates that hypothesis 1 should be partially accepted, stating that bias impacts loan officers' decision-making when assessing mortgage credit applications. More specifically, it seems likely that loan officers are biased towards applicants that have occupations that are socially considered as more prestigious.

5.1.2 Within Branches

		T-test	
		Casepair 1 [Occupation]	Casepair 2 [Age]
Branch 1	Credit Granted	0	0.567
	Interest Rate	0.224	0
	Perceived Risk	1.414	0.633
Branch 2	Credit Granted	1.058	1.000
	Interest Rate	0.210	0
	Perceived Risk	0.894	0.365
Branch 3	Credit Granted	1.981	0.643
	Interest Rate	1.413	0.022
	Perceived Risk	1.633	0.534

Table 4: T-test between cases within case pairs divided according to branch, with a critical **t-value of 2.132** for four degrees of freedom, see Appendix B for further details and Appendix D for t-table.

Hypothesis 2 states that bias affects branch-level decision-making when assessing mortgage credit applications. What can be stated and found by the statistical analysis in table 4 above is that none of the variables exhibit a statistically significant difference when comparing the different branches, indicating that hypothesis 2 should be rejected. However, illustrated in Table 4, it is also made apparent that *occupation* has a relatively stronger influence on decision-making on branch level when compared to *age*. This is similar to the previous section findings when examined amongst all loan officers, thereby strengthening the reasoning that loan officers might be more biased towards applicants who have occupations that are socially considered as being more prestigious.

Upon further analyzing the results, one can note that even if branch 3 grants higher credit and charges less interest rate compared with the other branches for applicants with occupations that are perceived as socially more prestigious, they subsequently set higher risk scores for these applicants. This is in contrast to common sense, where borrowers with higher perceived risk should pay a higher interest rate. Thus, there seems to exist, somewhat irrational, no connection between loan officers' assessment of inherent risk within an application and the interest rate given. This reasoning is strengthened when considering that the correlation between the two variables can be viewed as non-existent, $R^2 = 0.1$ see Appendix E.

In summary, no statistically significant impact of bias in terms of *occupation* and *age* was found to impact the branch-level decision-making. Even though the statistical analysis illustrates that *occupation* had a larger impact when compared to *age*.

5.2 Noise

5.2.1 Amongst Individuals

	Error [%]	Case 1	Case 2	Case 3	Case 4
Average	Credit Granted	9.37	5.66	3.14	10.64
	Interest Rate	8.22	8.88	8.19	6.93
	Perceived Risk	21.67	19.19	21.67	22.56
Max	Credit Granted	31.46	24.24	22.10	25.89
	Interest Rate	20.46	20.19	20.14	22.56
	Perceived Risk	53.13	63.14	62.50	42.31

Table 5: Summary of errors (relative approximation error) among all 15 loan officers.

Some interesting findings emerge upon analyzing the derived empirical findings regarding the existence of noise embedded within loan officers' decision-making, which is illustrated in Table 5. The large levels of noise make it reasonable to assume that loan officers set the interest rate somewhat randomly, or stated differently, that loan officers' decision-making is characterized as being subjective and based on the individual loan officers' judgment, rather than using an objective or standardized approach. In this regard, it is interesting to note that the correlation between capital granted and interest rate can be considered to be non-existing, $R^2 = 0.08$, see Appendix E. These findings have direct consequences for households. To illustrate, the difference in expenses for a household with a 4 000 000 SEK mortgage at a 1.65 versus 1.14 percent interest rate translates into a difference of 20 400 SEK in annual interest rate expenses, or put differently, 45 percent more or 31 percent less expenses when disregarding tax incentives.

That loan officers exhibit noise when faced with identical applications is also evident when analyzing the findings regarding credit granting. Although case 3 shows relatively lower levels of noise, the found variation can be exemplified by using case 1 where the answers ranged from a maximum value of 6 000 000 SEK and a minimum value of 4 000 000 SEK. Using a debt to value ratio of 85%, (the same that was used in the different cases) these findings mean that couples that are looking to buy a property can do so for approximately 7 000 000 SEK and respectively 4 700 000 SEK depending on which loan officer handles their case. Thus, the first property could cost 50 percent more than the latter. These findings regarding credit granted and interest rate suggests that households should expect relatively large variation in the amount that can be borrowed and to what interest rate.

The fact that the derived values concerning perceived risk stand out, can partly be explained by the scale that was used to measure this variable, which was a Likert scale ranging from 1 - very low risk to 5 - very high risk, thus, the answers that differ leads to relatively large levels of noise. With that being said, it does not explain the levels of noise found. The empirical evidence illustrates that loan officers' answers regarding perceived risk in cases 2 and 3, ranged from 1 to 4. This was to a great surprise, nonetheless when put in the context that banks and loan officers' most important task can be argued as constituting as accurately assessing and managing risk embedded within different financial instruments, including mortgages. Also, when considering that the Likert scale, which has been used to classify risk, is a realistic representation of a scale that financial institutions use in practice. Altogether, the findings indicate we should accept hypothesis 3, stating that loan officers exhibit noise when assessing mortgage credit applications.

5.2.2 Between Branches

Error [%]		Credit Granted Case 1	Case 2	Case 3	Case 4
Average	Branch 1	12.34	7.6	7.11	12.34
	Branch 2	2.72	2.53	0	8.29
	Branch 3	2.72	7.66	2.41	6.32

Error [%]		Interest Rate Case 1	Case 2	Case 3	Case 4
Average	Branch 1	6.41	8.92	8.92	7.08
	Branch 2	7.18	6.12	6.12	8.49
	Branch 3	9.07	8.57	6.51	5.38

Error [%]		Perceived Risk Case 1	Case 2	Case 3	Case 4
Average	Branch 1	14.55	11.43	18.46	17.78
	Branch 2	35.56	29.08	30.00	34.29
	Branch 3	20	10	13.33	0

Table 6: Summary of errors within the different branches.

Table 6 illustrates the level of noise existing within the different branches, across the different cases between the three different variables. As is evident from the empirical findings, the level of noise concerning the amount of credit granted is in general fairly high. However, one can note that branch 1 stands out with a higher level of noise. The findings also illustrate that case pair 1 (case 1 and 4) have slightly increased levels of noise in terms of credit granted when compared with case pair 2 (case 2 and 3). This is similar to previous findings made amongst all loan officers', thus strengthening the reasoning that it seems that *occupation* relative to *age* leads to an increased level of noise and thus, has a higher impact on loan officers' credit assessments.

The level of noise, or relative approximation error, among loan officers' also indicates the difficulty of proving statistical significant bias in terms of the mean difference. A larger error indicates a larger discrepancy amongst answers and therefore larger standard deviation within the group. As the standard deviation is in the denominator when calculating the t-value, see Section 3.5.1, increased standard deviation results in a lower t-value. Therefore, a branch that exhibits a high distribution of error requires a larger mean difference between cases for the difference to be statistically significant than a branch that exhibits a low distribution of error. As a result, the difference in mean between two cases within a case pair may be larger than the mean between two separate cases within another case pair, yet result in a lower t-value if the variation is larger within the first case pair. This might help explain why bias was not proven within more branches.

Regarding the variable interest rate, the analysis in table 6 exhibits a fairly similar level of noise when comparing the results derived from the different branches, thus, strengthening the previous reasoning that it seems that loan officers set the interest rate at what can be described as a random fashion. This is maybe not surprising when put in the context that Handelsbanken's strategy is built on using a highly decentralized and relationship-based approach, where individual branches are given much authority to make their own credit decisions. Perhaps more importantly, they seem to have a rather robust and standardized process to assess applicants' creditworthiness, but lack the same while setting interest rates. Differences in regards to the interest rate can have geographical explanations as well as for the fact that branches are faced with different competition, where loan officers use the interest rate as a negotiation mechanism to generate increased profitability. However, these factors seem unlikely to influence the derived empirical findings since the loan officers and branches that participated in the present study are located within the same geographical area but also since the loan officers answered questions derived from identical cases.

As illustrated in Table 6, the findings that loan officers show a large level of noise when it comes to assessing the level of risk inherent within the different applications is largely impacted by the found large levels of noise within branch 2. As previously stated, loan officers' most important task can be argued to be constituting the assessment of loan applicants' creditworthiness. This makes the empirical findings illustrating the existence of large deviations within the branches upon performing risk assessments somewhat surprising. Overall, the empirical findings illustrate the existence of relatively large levels of noise across the different branches, indicating that we should accept hypothesis 4.

6 Conclusion

This chapter presents the conclusions concerning the 4 stated hypotheses. It begins by explaining the research purpose and how this essay fulfills that. This is followed by the respective hypothesis and the conclusions connected to them. Lastly, the theoretical contributions of this study are presented.

The research purpose that this thesis addresses is a research gap in the lack of understanding human decision-making when it comes to bank loan officers' assessing credit applications. More specifically, the purpose was to measure the potential impact bias concerning age and occupation has on loan officers' decision-making capabilities and to measure the level of noise embedded within the process. This was done by measuring the impact on loan officers' decision-making for the variables credit granted, interest rate, and perceived risk. In fulfilling that purpose, the aim was to contribute to the ever-growing literature body concerning human decision-making. This was accomplished by testing four hypotheses:

Hypothesis 1:

Bias affects loan officers decision-making when assessing mortgage credit applications

In conclusion, bias does partially affect loan officers' decision-making in accordance with hypothesis 1. It can be stated that there is a statistically significant difference when it comes to the perceived risk of loan applications where bias concerning occupation was studied. The measured t-value was 1.969, which is above the critical t-value for a one-sided t-test at 95% confidence. This results in a statistically significant difference in terms of assessment between the two cases. In regards to capital granted and interest rate concerning the variable *occupation*, we could not find a statistically significant difference. The same can be concluded when it comes to the variable age. Therefore hypothesis one should partially be accepted.

Hypothesis 2:

Bias affects individual branches decision-making when assessing mortgage credit applications

In regards to the statistical analysis, it is made evident that bias concerning age or occupation could not be found to have a significant impact on individual branches' assessment of mortgage credit applications. No t-value exceeds the critical value of 2.132 for four degrees of freedom and 95% confidence. The closest is the t-value for branch 3.

Hypothesis 3:

Individual loan officers show differences in noise when assessing mortgage credit applications

Hypothesis 3 can be accepted based on the relative approximation error measurement that has been used to measure noise in this study since loan officers do indeed exhibit noise when assessing mortgage credit applications. There are similar levels of noise in all of the four cases, but there do exist higher levels of noise when it comes to perceived risk. This can arguably mean that the perceived risk of a credit applicant is more subjective than what credit is granted and the interest rate given and therefore leads to high levels of noise.

Hypothesis 4:

Individual branches show differences in noise when assessing mortgage credit applications

To conclude, hypothesis 4 can be accepted as well since individual branches show differences in noise when assessing mortgage credit applications, in many cases to a larger extent than what was anticipated. The level of noise between branches means in practicality that an individual looking to apply for a mortgage loan can expect relatively large variations in the amount of credit granted depending on the branch one applies at. Furthermore, the level of noise does have an impact on the received interest rate, which directly affects individuals' and households' personal finances. Also, the interest rate seems to be determined on a somewhat random basis, especially when looking at the almost non-existent correlation between interest rate and the other two variables: credit granted and perceived risk. Worth pointing out is that the level of noise can have a positive effect but also a negative effect, which makes the outcomes of loan applications seem random, even though they are to a great extent not.

	Bias	Noise
All individuals	*H1*: Partially true	*H3*: Accepted
Individual Branches	*H2*: Rejected	*H4*: Accepted

Table 7: Summary of verdicts for the four hypotheses.

To summarize, the theoretical contributions of this study further enhance our understanding of human decision-making and more specifically to what extent and how much bias impacts the credit assessment process and the level of noise embedded within the process. Not only on an individual level but also on a branch level, which makes the contribution more nuanced, which provides a more thorough understanding of the credit assessment process.

7 Discussion

This last chapter discusses the theoretical implications in connection to the problematization. Following that, the practical implications and managerial implications are reflected upon and discussed, which highlights the thesis relevance to the topic in general. Lastly, we suggest areas for future research.

The theoretical implications of the present study are further strengthening previous research findings by illustrating that human decision-making is best described as being bounded-rational, in contrast to being perfectly rational. Decision-makers limited and highly individual cognitive capabilities explain their tendency to exhibit bias and noise upon facing identical problems. The significance of further understanding decision-making processes involving humans is made apparent, but also to build upon methods to cope with these inconsistencies to further enhance processes. This, in order to create additional value when it comes to the business in general but also for its customers. An interesting aspect to lift is the possible other sociological and behavioral explanations there are that could explain the conclusions. For example, there could be cultural, personal, and managerial factors between the individuals and the different branches that also contribute to the stated outcome. These factors could and do possibly have, different effects on the overall business strategy in terms of intended vs. realized strategies, that could negatively and positively affect it due to the inconsistencies.

An interesting aspect, and perhaps a possible solution to human irrational decision-making, is using data and algorithms to efficiently remove humans out of the equation to achieve more consistent outcomes. However, in doing so, one also removes the additional customer value that organizations can gain from personal customer service, especially when it comes to mortgage credit assessments. Not to mention the fierce competition between different banks, where the interest rate offered between banks is something that is easy to compare for customers. Thus, Swedish banks use interest rate as a negotiation tool to attract customers which involves managing idiosyncratic or soft customer data. To do this, the current view is that a strategy involving loan officers is more favorable than using algorithms and AI, even though banks' investments in FinTech indicate this is going to change going forward.

The practical implications of the present thesis's empirical findings are that households that are applying for a mortgage can expect large variations in the amount of credit they can borrow and at what interest rate depending upon which individual loan officer or branch manages their application. Thus, this thesis can be used to visualize how bias and noise affect human decision-making and open up for opportunities to reduce it. Furthermore, it gives individual households an improved understanding of how the credit assessment process works. However, the fact that loan officers and branches exhibit noise while performing credit assessments was expected since it corresponds with previous research findings as well as the concepts of bounded rationality. On the other hand, what was rather surprising, was the levels of noise that exceeded our expectations. This suggests that the common belief that the credit assessment process is being performed in a relatively standardized and objective manner seems wrong.

The managerial implications is that managers within banks could gain new insights into their processes by being aware of human irrational decision-making and the consequences in terms of bias and noise. Furthermore, it is believed that methods and instruments in how to handle and measure the impact of bias and level of noise are vital in order for managers to start evaluating possible value-enhancing solutions. Solutions that could lead to more optimized processes and thus generate increased profitability. An example of a solution could be to use a more standardized process when assessing the credit applications or using more strict and clear guidelines for loan officers to follow.

The study also aimed to test the feasibility of applying a t-test when evaluating bias within a group. As there is no currently agreed-upon metric to decipher whether differences in human decision-making are due to bias or simply variation, we applied the premise of statistical significance between means. Although the t-test is a commonly applied metric within most fields concerned with data analysis or statistics, it assumes a perfect standard distribution within groups. As has been stated previously the credit granted among most officers was equivalent to 4.5 times applicants' annual gross income, often resulting in a small distribution around that specific assessment. For a small group of officers, there is a risk that all officers give the same assessment, resulting in no variation. If there is very low or no variation the result from the t-test becomes very high or incomputable, indicating extreme bias when in reality the low variation between answers is due to loan officers conventionally granting 4.5 times the applicant's gross income. This indicates a problem when using the t-test to evaluate bias within small groups with conventional standardized processes with low variation.

Any future research should consider:

- Evaluate if other factors impact bias and noise.
  This study considers bias and noise due to 'age' or 'occupation', yet there are multiple other factors that may impact the decision of individual loan officers' such as geographical differences in names.
- Applying the same methodology to separate banks.
  This study considers loan officers' within Handelsbanken, yet the methodology could be applied to any other bank.
- Applying the methodology to separate business fields.
  Many business fields use professional office clerks to make decisions surrounding specific cases in the same way banks do. Bias and noise within any such business could be evaluated using the same methodology. This could for example be done within the field of recruitment where the potential of being hired along with the specific salary may vary around specific parameters.

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Appendix A: Research Questionnaire

LUNDS
UNIVERSITET

Lånelöfte för bolåneansökan

Svaren på bolåneansökan utgör en del i ett examensarbete på Lunds universitet om kreditgivningsprocesser.

- Alla svar är anonymma
- Ansökan behandlas individuellt, <u>diskutera inte med varandra.</u>
- Fritt tillvägagångssätt

Bolåneansökan - avseende bostadsrätt

Syfte

Nedan presenteras fyra Case vilket baseras på att du har erhållit en ansökan om bolånelöfte. Där din uppgift är att läsa igenom presenterad information och därefter svara på tre frågor.

Förutsättningar

Utgå ifrån att det är en riktig låneansökan som du skall bedöma, utgå ifrån din yrkesroll när du analyserar informationen och svarar på frågorna

Case

Besvara hur stort lån du beviljar, risken du associerar till lånet och lånets ränta. Alla som ansöker om bolån har tillräckligt till kontantinsatsen (85% belåningsgrad). Utgå även ifrån att presenterad information är säkerställd, det vill säga, att information har verifierats genom lämpligt verktyg, UC, kontoutdrag eller anställningskontrakt.

Paren har inga barn.
Alla par har 200 000 SEK placerad i fonder (SHB MA100)
Inga kreditanmärkningar eller övriga skulder föreligger

Din ålder: _______ år Erfarenhet: _______ år
(inom kreditlångivning)

Ansökan I

	Sökande 1	Sökande 2
Namn	Love Eckhart	Elsa Simonsson
Ålder	39	35
Yrke	Svetsare	Vårdbiträde
Månadsinkomst (före skatt)	44 000	36 000

Beviljat lån: ____________ till ränta ______ % 3-mån rörlig

Risk: Väldigt Låg ○ Låg ○ Medel ○ Hög ○ Väldigt Hög ○

Ansökan II

	Sökande 1	Sökande 2
Namn	Erik Lööf	Emelia Strömberg
Ålder	22	21
Yrke	Elektriker	Flygvärdinna
Månadsinkomst (före skatt)	32 000	28 000

Beviljat lån: ____________ till ränta ______ % 3-mån rörlig

Risk: Väldigt Låg ○ Låg ○ Medel ○ Hög ○ Väldigt Hög ○

Ansökan III

	Sökande 1	Sökande 2
Namn	Roger Elofsson	Sussan Stenberg
Ålder	55	54
Yrke	Kock	Sjukgymnast
Månadsinkomst (före skatt)	34 000	26 000

Beviljat lån: ____________ till ränta _____ % 3-mån rörlig

Risk: Väldigt Låg ◯ Låg ◯ Medel ◯ Hög ◯ Väldigt Hög ◯

Ansökan IV

	Sökande 1	Sökande 2
Namn	Erik Jonsson	Lisa Lambertz
Ålder	36	34
Yrke	Advokat	Psykolog
Månadsinkomst (före skatt)	42 000	38 000

Beviljat lån: ____________ till ränta _____ % 3-mån rörlig

Risk: Väldigt Låg ◯ Låg ◯ Medel ◯ Hög ◯ Väldigt Hög ◯

Appendix B: Answers from Participants

All Individuals

		All participants			
		Case 1	Case 2	Case 3	Case 4
Average	Credit Granted [Mkr]	4.593	3.300	3.276	4.766
	Interest Rate [%]	1.403	1.448	1.448	1.346
	Perceived Risk [-]	2.133	2.733	2.667	1.733
Max	Credit Granted [Mkr]	6	4	4	6
	Interest Rate [%]	1.69	1.74	1.74	1.65
	Perceived Risk [-]	3	4	4	2
Min	Credit Granted [Mkr]	4	2.5	3	4.32
	Interest Rate [%]	1.2	1.25	1.29	1.150
	Perceived Risk [-]	1	1	1	1
Standard Deviation	Credit Granted [10^5]	5.830	3.135	2.106	5.824
	Interest Rate [10^{-4}]	0.148	0.153	0.140	0.133
	Perceived Risk [-]	0.640	0.704	0.724	0.458
Standard Error	Credit Granted [10^5]	1.505	0.809	0.544	1.504
	Interest Rate [10^{-4}]	3.825	3.961	3.604	3.442
	Perceived Risk [-]	0.165	0.182	0.187	0.118
Median	Credit Granted [Mkr]	4.32	3.24	3.24	4.35
	Interest Rate [%]	1.39	1.40	1.39	1.35
	Perceived Risk [-]	2	3	3	2

Table 8: Summary of answers among all 15 loan officers.

According to Branch

		Branch 1			
		Case 1	Case 2	Case 3	Case 4
Average	Credit Granted [Mkr]	5.108	3.516	3.396	5.108
	Interest Rate [%]	1.422	1.48	1.48	1.402
	Perceived Risk [-]	2.2	2.8	2.6	1.8
Max	Credit Granted [Mkr]	6	4	4	6
	Interest Rate [%]	1.65	1.74	1.74	1.65
	Perceived Risk [-]	3	3	3	2
Min	Credit Granted [Mkr]	4.32	3.24	3.2	4.32
	Interest Rate [%]	1.29	1.29	1.29	1.29
	Perceived Risk [-]	2	2	2	1
Standard Deviation	Credit Granted [10^5]	7.544	3.294	3.395	7.544
	Interest Rate [10^{-4}]	0.135	0.173	0.173	0.147
	Perceived Risk [-]	0.447	0.477	0.547	0.447
Standard Error	Credit Granted [10^5]	3.374	1.473	1.518	3.374
	Interest Rate [10^{-4}]	6.020	7.720	7.720	6.591
	Perceived Risk [-]	0.200	0.200	0.245	0.200
Median	Credit granted [Mkr]	5.40	3.40	3.24	5.40
	Interest Rate [%]	1.39	1.43	1.43	1.39
	Perceived Risk [-]	2	3	3	2

Table 9: Summary of answers within branch 1.

		Branch 2			
		Case 1	Case 2	Case 3	Case 4
Average	Credit Granted [Mkr]	4.292	3.292	3.240	4.556
	Interest Rate[%]	1.349	1.379	1.379	1.329
	Perceived Risk [-]	1.8	2.2	2.4	1.4
Max	Credit Granted [Mkr]	4.5	3.5	3.24	5.5
	Interest Rate [%]	1.59	1.59	1.59	1.59
	Perceived Risk [-]	3	3	3	2
Min	Credit Granted [Mkr]	4.32	3.24	3.24	4.32
	Interest Rate [%]	1.275	1.290	1.290	1.290
	Perceived Risk [-]	1	1	1	1
Standard Deviation	Credit Granted $[10^5]$	1.809	1.163	0	5.277
	Interest Rate $[10^{-4}]$	0.142	0.124	0.124	0.158
	Perceived Risk [-]	0.834	0.834	0.894	0.548
Standard Error	Credit Granted $[10^5]$	8.090	5.200	0	2.360
	Interest Rate $[10^{-4}]$	6.341	5.533	5.533	7.079
	Perceived Risk [-]	0.374	0.374	0.400	0.245
Median	Credit granted [Mkr]	4.32	3.24	3.24	4.32
	Interest rate [%]	1.29	1.35	1.35	1.29
	Perceived Risk [-]	2	2	3	1

Table 10: Summary of answers within branch 2.

		Branch 3			
		Case 1	Case 2	Case 3	Case 4
Average	Credit Granted [Mkr]	4.292	3.092	3.192	4.634
	Interest Rate [%]	1.438	1.484	1.486	1.308
	Perceived Risk [-]	2.4	3.2	3	2
Max	Credit Granted [Mkr]	4.32	3.24	3.24	5
	Interest Rate [%]	1.69	1.69	1.61	1.4
	Perceived Risk [-]	3	4	4	2
Min	Credit Granted [Mkr]	4	2.5	3	4.32
	Interest Rate [%]	1.2	1.25	1.35	1.15
	Risk [-]	2	3	2	2
Standard Deviation	Credit Granted [10^5]	1.809	3.309	1.073	3.410
	Interest Rate [10^{-4}]	0.182	0.170	0.120	0.097
	Perceived Risk [-]	0.548	0.447	0.707	0
Standard Error	Credit Granted [10^5]	0.809	1.480	0.480	1.525
	Interest Rate [10^{-4}]	8.121	7.541	5.297	4.317
	Perceived Risk [-]	0.245	0.200	0.316	0
Median	Credit granted [Mkr]	4.32	3.24	3.24	4.50
	Interest rate [%]	1.45	1.50	1.50	1.35
	Perceived Risk [-]	2	3	3	2

Table 11: Summary of answers within branch 3.

Appendix C: Error Amongst Participants

All Individuals

		All participants			
	Error	Case 1	Case 2	Case 3	Case 4
Average	Credit Granted [%]	9.37	5.66	3.04	10.64
	Interest Rate [%]	8.22	8.88	8.19	6.93
	Perceived Risk [%]	21.67	19.19	21.67	22.56
Max	Credit Granted [%]	31.46	24.24	22.10	25.89
	Interest Rate [%]	20.46	20.19	20.14	22.56
	Perceived Risk [%]	53.13	63.41	62.50	42.31
Min	Credit Granted [%]	0.65	1.58	0	2.89
	Interest Rate [%]	0.07	0.29	0.29	0.86
	Perceived Risk [%]	9.09	6.25	0	0
Median	Credit granted [%]	5.35	1.82	1.10	9.36
	Interest rate [%]	8.05	9.14	7.02	4.18
	Perceived Risk [%]	6.25	9.76	12.50	15.38

Table 12: Summary of errors among all loan officers' (N=15).

According to Branch

		Branch 1			
	Error	Case 1	Case 2	Case 3	Case 4
Average	Credit Granted [%]	12.34	7.60	7.11	12.34
	Interest Rate [%]	6.41	8.92	8.92	7.08
	Perceived Risk [%]	14.55	11.43	18.46	17.78
Max	Credit Granted [%]	17.46	13.77	17.79	17.46
	Interest Rate [%]	16.03	17.57	17.57	17.69
	Perceived Risk [%]	36.36	28.57	23.08	44.44
Min	Credit Granted [%]	5.72	3.30	2.83	5.72
	Interest Rate [%]	2.26	3.38	3.38	0.86
	Perceived Risk [%]	9.09	7.14	15.38	11.11

Table 13: Summary of errors within branch 1.

		Branch 2			
	Error	Case 1	Case 2	Case 3	Case 4
Average	Credit Granted [%]	2.72	2.53	0	8.29
	Interest Rate [%]	7.18	6.12	6.12	8.49
	Perceived Risk [%]	35.56	29.09	30.00	34.29
Max	Credit Granted [%]	6.80	6.32	0	20.72
	Interest Rate [%]	17.87	15.30	15.30	19.64
	Perceived Risk [%]	66.67	54.55	58.33	42.86
Min	Credit Granted [%]	0.65	1.58	0	5.18
	Interest Rate [%]	0.07	0.29	0.29	1.58
	Perceived Risk [%]	11.11	9.09	16.67	28.57

Table 14: Summary of errors within branch 2.

		Branch 3			
	Error	Case 1	Case 2	Case 3	Case 4
Average	Credit Granted [%]	2.72	7.66	2.41	6.32
	Interest Rate [%]	9.07	8.57	6.51	5.38
	Perceived Risk [%]	20	10	13.33	0
Max	Credit Granted [%]	6.80	19.15	6.02	7.90
	Interest Rate [%]	17.52	15.76	9.15	12.08
	Perceived Risk [%]	25	25	33.33	0
Min	Credit Granted [%]	0.65	4.79	1.50	2.89
	Interest Rate [%]	0.83	1.08	0.94	1.38
	Perceived Risk [%]	16.67	6.25	0	0

Table 15: Summary of errors within branch 3.

Appendix D: T-table

	Confidence		
df	90%	95%	97.5%
1	3.078	6.314	12.71
2	1.886	2.920	4.303
3	1.638	2.353	3.182
4	1.533	2.132	2.776
5	1.476	2.015	2.571
6	1.440	1.943	2.447
7	1.415	1.895	2.365
8	1.397	1.860	2.306
9	1.383	1.833	2.262
10	1.372	1.812	2.228
11	1.363	1.796	2.201
12	1.356	1.782	2.179
13	1.350	1.771	2.160
14	1.345	1.761	2.145
15	1.341	1.753	2.131

Table 16: One-sided unpaired t-table for 15 degrees of freedom with three levels of confidence.

Appendix E: Regression Analysis

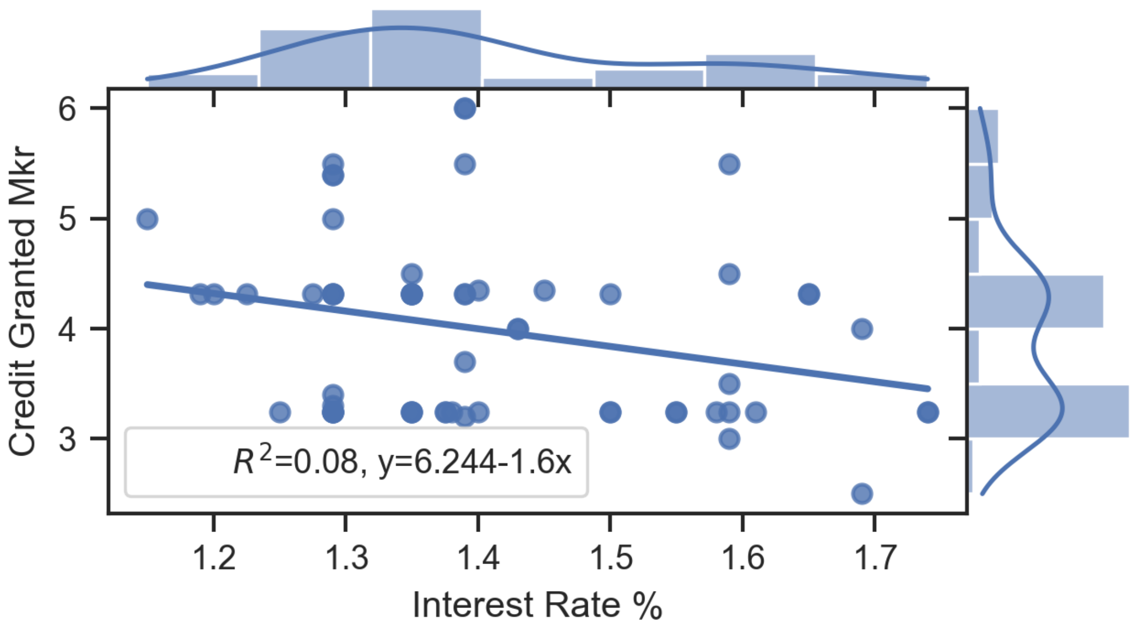

Figure 12: Linear regression with the dependent variable credit granted and the independent variable interest rate.

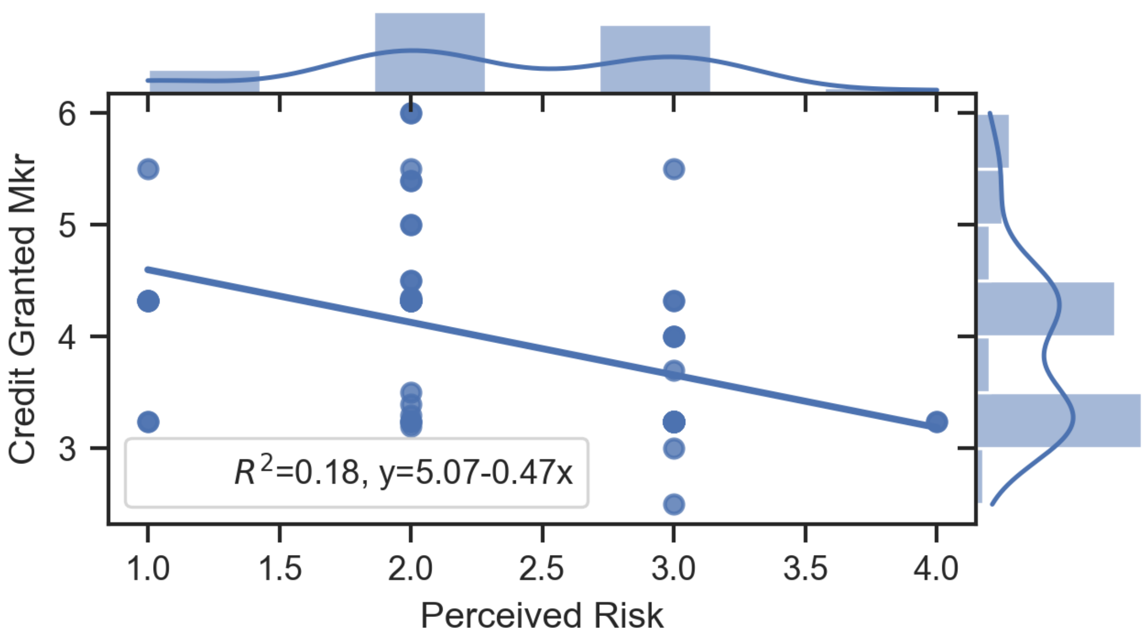

Figure 13: Linear regression with the dependent variable credit granted and the independent variable perceived risk.

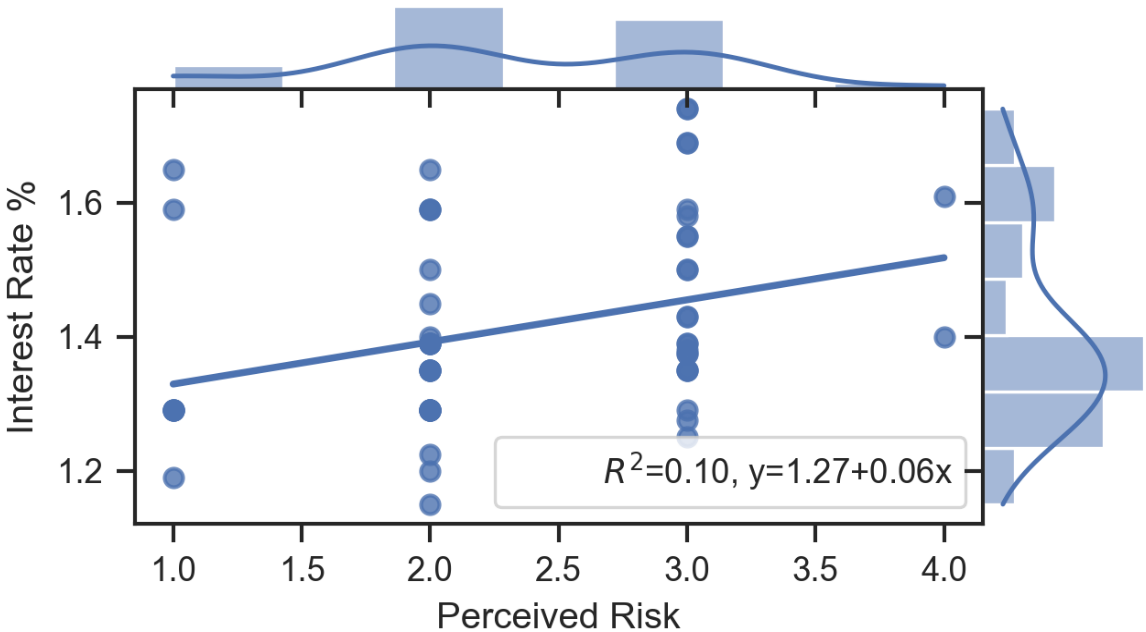

Figure 14: Linear regression with the dependent variable interest rate and the independent variable perceived risk.