University of Economics, Prague

Master’s Thesis

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University of Economics, Prague

Faculty of Business Administration

Master´s Field: International management

Title of the Master´s Thesis:

Development of a Digital Model for Customer Credit Limit Decisions: Identification of Impact of Macroeconomic Indicators on Credit Risk Assessment

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Declaration of Authenticity

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Prague, May 16, 2018 Signature

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Abstract:

A solid credit risk management in corporations is key to minimize financial risk. Due to the fourth industrial revolution, credit risk management processes change from manual proceeding to automation with credit scoring showing high potential for advanced analytics. This thesis analyzed the importance of considering macroeconomic indicators within a credit scoring model. The research methodology based on two surveys with credit risk communities and a statistical analysis including a correlation and regression analysis proved the importance of the external information within a credit scoring model with differences among the analyzed regions. Despite that, further statistical testing is suggested to identify a set of the most relevant macroeconomic indicators once the underlying credit scoring model is further developed.

Key words:

Credit Risk Management, Credit Scoring, Industry 4.0, Macroeconomic indicators, Automation

Table of Contents

List of Figures

List of Tables

List of Equations

List of Abbreviations

AI	Artificial Intelligence
B2B	Business to Business
CIS	Commonwealth of Independent States
CPI	Consumer Price Index
CPPSs	Cyber-Physical Production Systems
CRM	Credit risk management
D&B	Dun & Bradstreet
DA	Discriminant Analysis
DSO	Days‘ Sales Outstanding
EMEA	Europe, Middle East & Africa
EU	European Union
FCIB	Finance, Credit & International Business Association
FIS	Fidelity National Information Services Inc.
FSCM	Financial Supply Chain Management
GDP	Gross Domestic Product
GDPR	General Data Protection Regulation
IoT	Internet of Things
IT	Information Technology
MLE	Maximum Likelihood Estimation
NNs	Neural Networks
PwC	PricewaterhouseCoopers
S&P	Standard & Poor’s
UAE	United Arab Emirates
UK	United Kingdom
US	United States

1. Introduction

1.1. Background and Motivation

Every business transaction without an advanced payment from a customer bears a certain degree of risk related to late or non-payment, called credit risk. In the corporate environment, the degree of risk highly depends on the customer’s financial situation and the outlook of the economy. Staying competitive in today’s business, it is impossible to eliminate credit risk by not offering sales on credit. Therefore, a proper credit risk management (CRM) is important to minimize potential losses due to the non-settlement of the receivables.

During the financial crisis in 2008, not only the financial industry but also corporations realized the significance of credit risk and its impact on a corporate’s liquidity. Taking this recession as a trigger point, many corporations implemented internal credit risk management departments and developed processes from proper customer acquisition and assessment to receivable management and standardized debt collection (Langkamp, 2014, p. 1).

In the course of the fourth industrial revolution and the need for digitalization of processes, the optimization of the credit scoring process came more and more to the fore. The internet of things and digital interfaces to external business partners and services could improve the data availability used for a credit risk assessment while machine learning algorithms could increase the predictability and accuracy of an assessment. A shift from manual to automated processes enables credit managers to focus on decision making and future-oriented tasks (The Economists, 2017).

Company XYZ undergoes a corporate transformation within the corporate-wide digital initiative. Starting with a focus on smart manufacturing and logistics, the company widened its actions due to the reason that a digital transformation can only be successful when rolled out company-wide. The treasury department, being a business partner to all different business functions within the company, especially focuses on predictive analytics. The credit risk department develops an automated credit scoring and credit limit determination process to reduce the handling of a large customer base yet contributing only to a proportionally small part of the credit limit exposure. The machine learning algorithm is based on internal data such as payment behavior or internal ratings limiting it to internal experiences with the customer.

Anderson (2007) is just one of the various authors pointing out that economic upturns or downturns such as changes in interest rates, inflation or employment have a significant impact on the customer's payment behavior. Another example provided is the financial crisis which had a significant impact on many firm's liquidity. Due to the globalized markets and the fast-changing economic developments, many banks have already included macroeconomic factors within their scoring models serving as a best practice example for corporations. The digitalized ecosystem and the advanced technology have made the inclusion of economic information due to direct interfaces with external providers as feasible as never before.

1.2. Objective

After the financial crisis 2008, the topic of credit risk management grew significantly in importance. Many corporations have started to integrate credit risk management departments being responsible for customer credit analysis and the determination of internal ratings and credit limits.

Additionally, in scope of the age of Industry 4.0, businesses see potential in optimizing processes to increase efficiency and effectiveness. Automated credit limit decisions became in scope of Company XYZ due to several reasons. The main current challenges are high efforts for small customers and manual proceedings of finance for collecting and maintaining information. Automated credit decisions based on score predicting future behavior of customers ensure less manual efforts and a higher focus on most relevant customers.

Literature on credit scoring suggests taking into consideration various aspects when analyzing a customer. Knowledge on the customer's financial and management risks, the loan structure including past payment behavior and exposure as well as industry and environment issues are required. Company XYZ's scoring model is based on statistically proven predictive analytics based solely on microeconomic data such as customer payment behavior, exposure and rating information. The aspect regarding the macroeconomic environment is not yet considered within the developed model. The thesis therefore discusses two main objectives. First, the aim of the thesis is to analyze the importance of macroeconomic indicators for a credit risk assessment. It will discuss and measure whether macroeconomic aspects should be considered within the scoring model in order to improve the assessment of a customer's creditworthiness. As the proceeding of credit limit determination changes from manual to automatic procedure due to the pressure of the new industrial revolution, the second objective of the thesis is to discuss what impact Industry 4.0 could have on credit decisions and the evaluation of the customer’s creditworthiness.

1.3. Outline

The diploma thesis starts with introducing the topic credit risk management by providing an overview of credit risk definitions and specific sources of credit risk. The chapter provides an overview of the credit risk management process and embeds credit scoring and credit limit determination within the overall process. This first chapter serves as a basis, underlines the importance of credit risk management within a corporation and provides an understanding of the process steps *credit scoring* and *credit limit determination*.

Continuing, the author summarizes the theory on statistics used in credit scoring to elaborate on the techniques and especially on the changes from traditional credit scoring to the advanced methods. Furthermore, the chapter introduces a practical example on Credit Scoring within Company XYZ as the data for the statistical analysis is going to be based on the credit scoring model results. The company faces many digitalization projects including the automation of credit risk assessments.

After providing an overview of credit risk management, the steps within a CRM process and the credit scoring techniques in detail, the fourth chapter outlines the differences in credit risk among different regions. It introduces the topic of macroeconomic indicators as a factor influencing credit risk and a customer’s payment behavior. The purpose of this chapter is to analyze the importance of macroeconomic indicators within a customer credit risk assessment as well as the identification of relevant indicators seen by field experts.

The next chapter describes the statistical analysis. It uses the pre-defined macroeconomic indicators and tests the correlation with the customer payment behavior to identify whether it is significantly relevant to include macroeconomic indicators within the scoring model.

Finally, the thesis embeds the optimized automated process of credit limit determination within the topic of Industry 4.0. Due to the on-going digitalization and the related pressures for companies to optimize their processes to stay competitive, the chapter identifies the impact of Industry 4.0 especially for credit risk management. It first defines the term Industry 4.0 followed by outlining the impact with regards to the advantages and drawbacks of digitalization for customer credit risk management. Concluding, a comprehensive evaluation of the results and an overview of the next steps is going to end the thesis.

1.4. Methodology

The research methodology on which the thesis is based can be divided into two main parts: theoretical part and practical analysis. The following paragraphs will outline the different approaches used (cf. Figure 1).

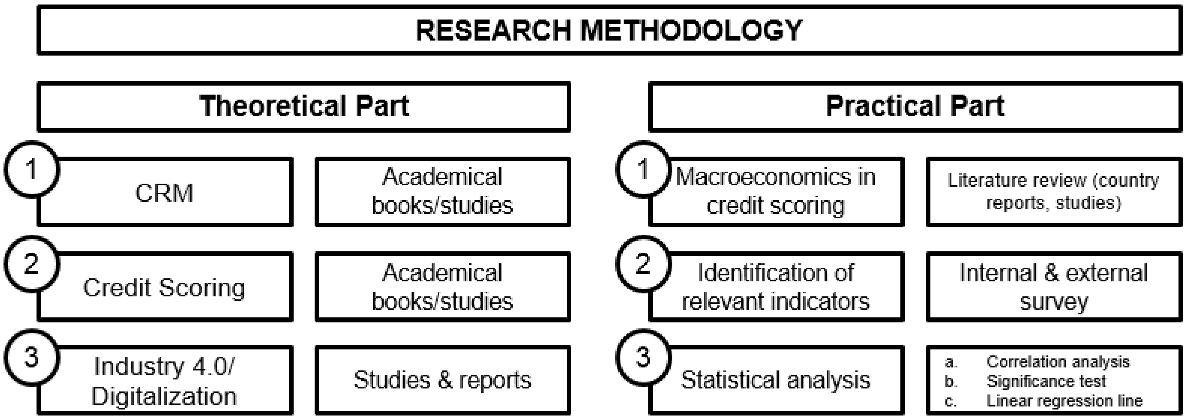


Figure 1 Diploma Thesis Research Methodology (created by author)

The literature review on the topics credit risk management, statistics in credit scoring and Industry 4.0/Digitalization is based on secondary research. Especially for the topics CRM and credit scoring mainly academical books and studies are used. This provides a basic understanding of the processes and methodologies within CRM. Given the topicality and newness of the topic Industry 4.0/Digitalization, the main sources used by the author within the research have been studies and reports from advisory companies specializing on the topic.

The practical part of the thesis can be divided into a three-step approach. The aim of the analysis is split. First, it aims to identify relevant macroeconomic indicators for a credit risk assessment and secondly, it aims to find out whether macroeconomic indicators should be considered within the credit scoring model. The first step within this part is the identification of the macroeconomic indicators. For this, the author conducts a literature review using country reports and studies to identify differences within the regions in Europe, Middle East and Africa and to identify a potential list of relevant indicators within credit risk management. The second part is a survey conducted with a CRM community inside and outside the company. This provides an overview of macroeconomic indicators identified as important by internal and external credit managers. After the identification of relevant indicators, the last step is the statistical analysis. The author conducts a linear regression analysis on which three aspects can be analyzed. The author first checks the correlation between the identified indicators and the customer classification into two main classes, good and bad, representing the payment behavior, followed by a significance test of the correlations. After this, a regression line is formulated for the significant correlated indicators. The analysis is based on a country- and regional level to evaluate regional differences.

The practical realization of the study was supported by two main software programs, Microsoft Excel and the statistical program R. Especially the last-mentioned software enabled the analysis of the large data base. The surveys were conducted using Microsoft Word, Excel and the online service SurveyMonkey. The detailed reasons for the choice of systems will be explained within the fourth chapter.

2. Credit Risk Management

Credit is an unavoidable topic in almost every business. It does not only support economic growth, it also allocates capital and wealth adequately. It enables economic transactions which could not be possible due to the lack of investment opportunities. Credit is often granted by financial intermediaries which can vary from investment banks, over savings and loan associations to financial companies. These intermediaries determine who can get a credit and for what price. The transaction includes two parties: the intermediary taking the position as the creditor and the obligor getting the loan (Koulafetis, 2017, p. 1).

Within the last years, the importance of credit increased significantly with the downside of a risk increase as well. After the financial crisis, the pressure on financial institutions and corporate finance organizations grew due to the unavoidable correlation between credit and risk. A solid analysis of a borrower’s creditworthiness is necessary to manage lending successfully (Fight, 2004, p. 1). The following chapter elaborates on credit risk including its definition, processes and management.

2.1 Definition & Sources of Credit Risk

Every business transaction encounters many types of different market uncertainties which give rise to financial risks. Financial risks occur due to changes in the financial market and can vary from foreign exchange risk, interest rate risk, commodity price risk, equity price risk, operational risk to credit risk (Horcher, 2005, pp. 23-24). A literature review on credit risk provides a long list of definitions, four of them are presented in Table 1. When comparing the various definitions, it is possible to identify commonalities. A transaction between two parties, namely the obligor and the creditor, can result in a financial loss for the creditor giving rise to in credit risk. The loss arises due to one of three reasons: a delayed payment, the unwillingness of an obligor to pay at all or the inability to pay due to illiquidity or insolvency.

Table 1 Overview of definitions of Credit Risk (created by author)

Definition Credit Risk
„Credit risk can be defined as the risk of financial loss due to the borrower's, bond issuer's or counterparty's (the "obligors") failure to honor their financial obligations. The obligors' failure to honour their obligations can arise due to inability or unwillingness." (Koulafetis, 2017, p. 2)
„Credit risk is the possibility of losing money due to the inability, unwillingness, or nontimeliness of a counterparty to honor a financial obligation. Whenever there is a change that a counterparty will not pay an amount of money owed, live up to a financial commitment, or honor a claim, there is credit risk." (Bouteillé & Coogan-Pushner, 2013, p. 3)
„Credit risk is basically the extent of the possibility that the contractor is insolvent in whole or in part in fulfilling the obligation. Any type of a loan can provide this kind of risk, even if granted in technically correct forms and with adequate guarantees. Moreover, it is necessary to underline the fact that the risk in question is not determined only by the insolvency of the borrower, since to the bank even a simple delay of the loan repayment can be detrimental." (Modina, 2015, p. 21)
„Credit risk is one of the most prevalent risks of finance and business. In general, credit risk is a concern when an organization is owed money or must rely on another organization to make a payment to it or on its behalf. […]. Default risk arises from money owed, either through lending or investment, that the borrower is unable or unwilling to pay." (Horcher, 2005, pp. 39-40)

One can encounter credit risk in all various types of transactions. According to S. Bouteillé and D. Coogan-Pushner, there exist seven types of transactions facing credit risk namely loaned money, lease obligations, receivables, prepayment for goods and services, deposits, claims and contingent claims on assets and derivative (Bouteillé & Coogan-Pushner, 2013, pp. 5-7) (Appendix A). This thesis only focuses on the transaction of receivables and the interrelated credit risk.

Accounts receivables are one of the main drivers of credit risk in corporations. A receivable “is any claim for money, goods, or services which have been earned or paid for but not yet received. Accounts receivables are usually non-written promises to pay for goods or services, normally extended for 30 to 60 days, and represent usually open accounts.” (Sharma, 2008, p. 120). The importance of sale on credit increased within the last years. It is impossible to be successful and stay competitive without offering credit sale. However, the flip side of trade credit is the impact of a default event which occurs when a buyer either pays late or does not pay at all (Koulafetis, 2017, pp. 4-5). Accounts receivables are an important part of a firm’s working capital management. Working capital management is a significant financial issue within a firm as it helps a company to manage its day-to-day business. Without efficient working capital management, a company might lack liquidity which can happen due to difficulties collecting its accounts receivables. Working capital is defined by subtracting the current liabilities from the current assets. This number identifies whether a company can settle its short-term obligations with its current assets. Balancing the level of working capital is therefore of high importance. There are various dangers of having either too much or too little working capital listed by Sharma (2010). One drawback of having too many receivables is a higher necessity of supervision and good amount of control implying higher costs. However, having too little working capital can also lead to illiquidity or production shortage. Moreover, in an event of emergency, a company would be dependent on more expensive external financing than using its own cash tied in open but unsettled credit sales. Therefore, accounts receivables, as being part of the working capital, need to be managed efficiently as it contributes significantly to the overall cash flow of a company. Therefore, many corporations aim to develop policies and a suitable organizational set-up to ensure a constant and ongoing CRM (Sharma, 2008, pp. 25-27;120) (Sagner, 2010, pp. 89-94).

The credit risk associated with accounts receivables has one important factor which gives rise to hope for corporations and its working capital management – its controllability. Credit risk does not arise out of nowhere. Corporations have the ability to track the exposures, they know to whom they offer credit sale and they have experiences with certain customer’s payment behavior. This is why a solid credit risk management within a corporation is of high importance in order to minimize the risk exposure (Bouteillé & Coogan-Pushner, 2013, p. 18) (Koulafetis, 2017, pp. 13-14).

Credit Risk Management can be defined as „an integrated system of models and measurement tools that allows, along with the existence of appropriate organizational structures, a finalized and optimal management of the credit risk." (Modina, 2015, p. 21). Considering the different parts of the definition, successful credit risk management should not only have appropriate models, processes and tools in place but also appropriate organizational structures ensuring clear responsibilities. Corporations handle the organizational set-up differently. One possibility is a Shared Service Center Credit Unit. This provides the advantage of standardized processes leading to higher efficiency. The second organizational set-up is a credit risk department within the corporate treasury. Corporate treasury acts as the bank within an organization ensuring sufficient liquidity for the ongoing and future business. It includes for example customer and corporate financing, leasing, asset management and risk management. A corporate treasury function is normally organized centrally, distant from the customer. Customer credit analysis however requires a good understanding of the customer, the situation and the country which is the reason for why there is often a local treasury credit unit. The third option to integrate credit risk management is within the corporate controlling or accounting function taking the advantage of already established controlling and communication principles. In case a corporation is constantly confronted with long maturities and highly risky customer financing, it is even possible to set up an own corporate credit risk organization. Companies with capital intensive and complex products implement such an organizational structure. In practice, it is difficult to clearly differentiate between the just-described organizational set-ups. Especially large corporations implement hybrid models such as a centralized corporate credit risk organization focusing on the overall picture of credit risk with regional credit units being responsible mainly for the communication with the customer (Langkamp, 2014, pp. 39-46).

As already mentioned before, a solid credit risk management depends not only on an appropriate organizational set-up but also on the integrated system of tools and processes. The important steps and processes of CRM will be described in the following sub-chapter.

2.2 Processes

An integrated credit management process in corporations consists of six main phases and further sub-processes which will be elaborated in the following paragraphs (Weiß, Stach, & Leick, 2011) (cf. Figure 2).

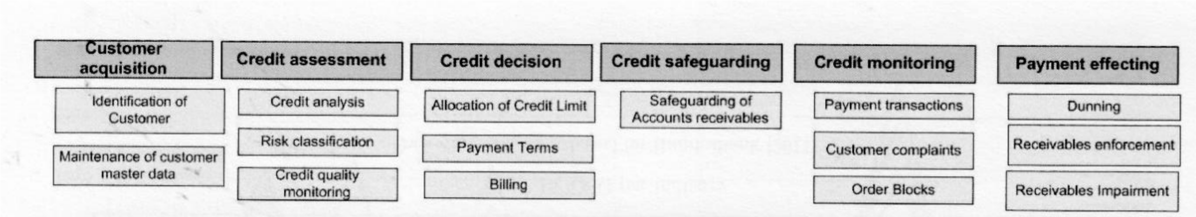


Figure 2 Phases and processes of Credit Management (Langkamp, 2014, p. 122)

<u>Customer acquisition</u>

The first step in the process of credit risk management is the customer acquisition which serves as the foundation for the whole process. Relevant customers need to be identified with regards to the business potential and the financial situation as well as the importance of relationships to start monitoring potential future payment defaults and avoid potential losses from the beginning of the process. Several sources like credit rating agencies or trade registers provide information to get a first impression of the business partner. It serves as a first step in the customer selection process (Weiß, Stach, & Leick, 2011, p. 8).

The second major process within the customer acquisition phase is the maintenance of customer master data. The master data builds the administrative basis for internal company processes like sending invoices, addressing the right contact person or billing the right entity. In order to avoid subsequent errors within the processes, a high accuracy and ongoing maintenance are of high importance (Verein für Credit Management e.V., 2007, pp. 11-12).

<u>Credit assessment</u>

During the credit assessment phase, a credit analyst follows three steps: Credit analysis, risk classification and credit quality monitoring. This process has the objective of evaluating the customer’s creditworthiness defined as the ability to pay callable obligations and tries to estimate the probability of credit default which is important for further processes such as the determination of credit limit or payment terms. Based on the credit analysis’ results, it is necessary to assign a rating representing the overall risk (Weiß, Stach, & Leick, 2011, pp. 9-11). Corporations can either use external ratings provided by rating agencies like Standard & Poor’s or Moody’s or they can implement their own internal rating approach. Often, it is typical to use both, internal and external ratings, for an extensive customer analysis.

Credit decision

The phase of credit decision serves as the “insurance” or “safeguarding” within the overall process. Within this phase, each customer is allocated a credit limit with two major functions. First, it prevents a customer from buying an infinite number of products without settling any obligations protecting the company from losses due to payment defaults. Second, it provides information on the customer’s creditworthiness, which is interrelated to the just described phase of credit assessment (Weiß, Stach, & Leick, 2011, p. 16).

Assigning a credit limit to a customer is not the only task within the process. Monitoring the credit limit exposure plays an important role. In case a customer reaches a credit limit, it is the credit managers’ responsibility to take respective actions by either expanding the credit limit or blocking future orders (Verein für Credit Management e.V., 2007, pp. 8-9).

Within the process of credit decision, the determination of the payment terms plays a role as well. The payment term regulates the due date of the payment. This often causes a conflict of interests between the vendor and the customer. The customer aims to keep its cash and liquidity high asking for longer payment terms. The vender takes the opposite position due to the same reasons. Payment term negotiations are part of the daily business (Weiß, Stach, & Leick, 2011, p. 16)

Billing, the last process in the credit decision phase, goes hand in hand with the requirements on customer master data. Correct billing avoids rise in credit risk and non-payment due to internal mistakes. (Verein für Credit Management e.V., 2007, p. 10). As the thesis focuses on these two phases of the risk management process, it will be further elaborated in the following subchapter.

Credit safeguarding

An internal customer analysis is not the only option to minimize the credit risk. Especially for very risky customers, a corporation has the possibility of implementing further safeguarding activities like sureties (guarantees) and trade credit insurances. The implementation of such measures often depends on the customer’s environment and type of business (Weiß, Stach, & Leick, 2011, pp. 17-19).

Credit monitoring

As mentioned earlier, a corporation needs to monitor the credit limit exposure as well as the outstanding obligations constantly. Exceeding a credit limit might lead to order blocks impacting the customer relationship. Complaints affect the company negatively. Keeping the complaints and the costs for this process as low as possible, fast actions are required (Pfaff, Skiera, & Weiss, 2004, pp. 152-157).

Payment effecting

The last phase within the credit risk management process is the payment effecting including processes like dunning, receivables enforcement and receivable impairment. Corporations often implement standardized processes of dunning and collection with the aim of reminding the customer of open overdue obligations and of taking all necessary requirements to be allowed to hand over the claim to legal (Weiß, Stach, & Leick, 2011, pp. 152-155).

2.3 Credit Scoring and Limit Management

C. Langkamp (2014) defines in his dissertation that credit risk management in corporations is not solely a risk but a profitability management containing a risk component. The most important component of the risk management process is the determination of the credit limit as it manages the open obligations and limits the risk of non-settlement (Langkamp, 2014, p. 96). The credit limit determination is based on the credit assessment of a customer identifying the creditworthiness which is called credit scoring. Therefore, the two steps go hand in hand and will be discussed in the following as they build the basis for the analysis of the thesis.

Getting information on a customer is key and builds the foundation for the credit scoring and limit determination. There are different elaborations on how to structure the necessary information. One of the first tools developed in this field is the *5Cs of credit* by John E. Baiden, namely Capacity, Capital, Conditions, Character and Collateral. *Capacity* describes the customer's ability to pay back the obligation from the available income. *Capital* stands for the financial resources a customer has on hand for unpredictable events. The third C for *Conditions* elaborates on the environment which might influence a firm's payment behavior. The analysis of a firm's management team is summarized by *Character* and the last aspect, *Collateral*, describes the securities that can be provided like assets or guarantees from a third party (Anderson, 2007, p. 122) (Fogle, n.d.). Another possibility to structure the risk assessment is by dividing it into a quantitative and qualitative assessment. The quantitative assessment includes the company's financial analysis, past payment behavior and exposure while the qualitative assessment focuses on the general information (background of the company, the underlying transaction, the relationship with the customer, external ratings) as well as the political, macroeconomic and regulatory environment (Bouteillé & Coogan-Pushner, 2013, pp. 79-90). Fight (2004) lists similar aspects to consider in a credit analysis including the financial statements, the business environment, the facility management and the enforceability (e.g. availability of guarantees). Summarizing the literature, it is possible to cluster the parts which need to be taken into consideration when analyzing a customer as shown in Figure 3.

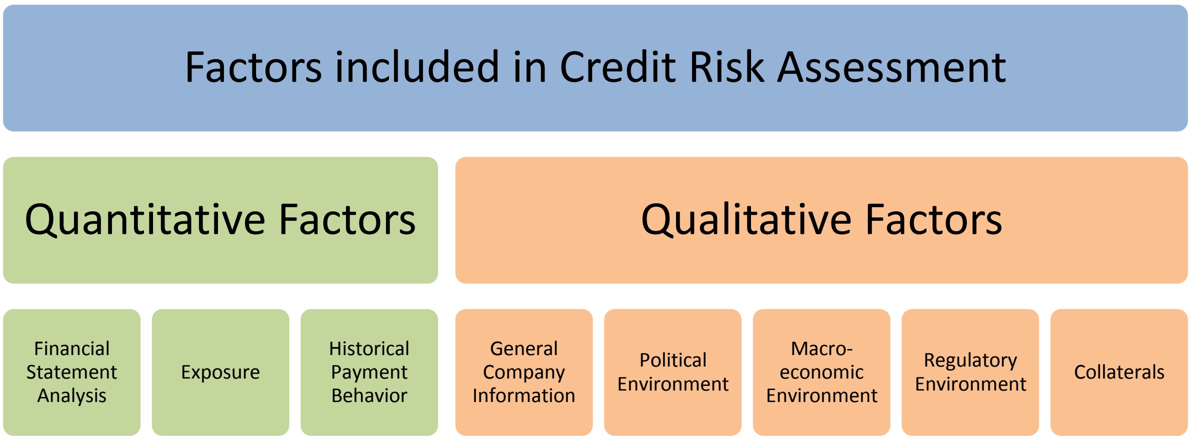


Figure 3 Factors included in Credit Risk Assessment (created by author)

Solely possessing the information is not enough to minimize the credit risk. A detailed analysis is key to identify the risk and establish a strategy on how to cope with the risk exposure. There are basically two approaches which can be used, the judgmental or the scoring approach. The judgmental technique is an evaluation done by a decision maker called the creditor. This technique builds on the expert experience and gained knowledge of the credit manager implicating on the other side a subjective decision which might be influenced by personal preferences and opinions. On top of that, corporations with a large customer base would face a high workload when analyzing each customer individually (Bailey, 2004) (Sullivan, 1981).

The second technique is the credit scoring. Credit scoring is defined as „the use of statistical models to determine the likelihood that a prospective borrower will default on a loan. Credit scoring models are widely used to evaluate business, real estate, and consumer loans" (Gup & Kolari, 2005, p. 508). It consists of different steps including

„collecting, analyzing and classifying different credit elements and variables to assess the credit decision." (Abdou & Pointon, 2011, p. 2). The term credit scoring consists of two words whose meaning can be discussed separately as suggested by Anderson (2007). Credit, to pick up the term again, means to buy a product or service now but pay later. Getting a credit is often seen as a right by many people, but it goes along with an obligation. The obligor needs to pay back the amount, needs to create a basis of trust and might need to pay a premium for the possibility to pay. This determines the creditworthiness and credit risk as already outlined earlier. The second word scoring expresses a numerical tool which analyses the available data, ranks them and assigns a score. Combining the two explanations, Anderson provides a similar definition to Gub and Kilari (2005): Credit scoring is "the use of statistical models to transform relevant data into numerical measures that guide credit decisions." (Anderson, 2007, pp. 5-7).

Credit scoring is mostly preferred by organizations over the judgmental technique because of its benefits. The scoring technique is based on objective criteria and considers only those variables being relevant for the evaluation of the customer's creditworthiness. Moreover, statistical models can take into consideration much more information than a credit analyst could consider manually (Abdou & Pointon, 2011, pp. 4-5). It also enables credit managers to focus on the relevant and riskier customers. Another advantage is the reduction of credit process costs and fewer errors due to the avoidance of personal biases (Al Amari, 2002). As credit scoring models are based on statistical techniques, it can have the drawbacks of classification errors (which will be elaborated at a later part of the thesis). Due to this misclassification, it can happen that a customer with a good payment behavior will be rejected or a bad customer will be classified as good, leading to profitability losses. Moreover, the development of scoring models requires expert knowledge on statistics which can be costly. A frequent maintenance and update is necessary to ensure adequate and updated data inputs and to correct errors made by the model (Abdou & Pointon, 2011, p. 5) (Al Amari, 2002, p. 69).

The credit scoring is only one important part to mitigate the credit risk. The second part as mentioned earlier is the credit limit determination. A credit limit is defined as „the absolute dollar (or other currency) amount of risk that a company wants to take, or, in other words, the maximum loss that a company is prepared to withstand." (Bouteillé & Coogan-Pushner, 2013, p. 25). With the help of the scoring model, it is not solely possible to identify whether to accept or reject a customer but to assess the creditworthiness and evaluate based on this what risk a corporation is willing to take. This decision will be represented by the credit limit. The limit is equal to the maximum exposure a customer can exploit. Usually, corporations determine within their credit management guideline a credit limit decision matrix classifying the customers based on the results of the scoring model and determining the appropriate credit limit (Langkamp, 2014, pp. 96-98).

In general, the scoring and the credit limit determination are essential parts of the credit risk management process and contribute to the minimization of the risk. The importance and the necessity of these techniques especially with regards to the increasing amount of information available due to new technologies can be underlined by a concluding citation of Herbert Alexander Simon to this chapter:

„What information consumes is rather obvious; it consumes the attention of its recipients. Hence, a wealth of information creates a poverty of attention, and a need to allocate that attention efficiently among the overabundance of information sources that might consume it." (Simon, 1971).

3. Credit decisions based on statistics

The second chapter already pointed out the importance of credit scoring and credit limit determination within the overall CRM process. Credit scoring can be based on manual handling or – with an increasing importance within the last years – automatically. This chapter picks up the topic credit scoring again but with focus on the use of statistics. After summarizing the theory, the chapter provides one specific example in practice on how statistical models are used within the development of a credit scoring model.

3.1. Literature review of statistics in credit limit decisions

Summarizing the description of credit scoring of chapter two in one sentence, it can be defined as an algorithm predicting cases namely customers of either being good or bad payer in the future. As future decisions and actions are dependent on the output of the algorithm, the biggest challenge is the data dependency. The underlying data used for the predictive model determines how good the model predictability is. According to Anderson (2007), there are four main aspects to consider. The first aspect is the data transparency meaning that the model needs useful information for decision making. The second aspect is the structure. The data needs to be structured and in a data format, that can be processed by the model for the analysis. The third aspect is data quantity going hand in hand with the data quality, the fourth aspect. Not only the data accuracy, completeness and relevance is important but also the sufficiency of good and bad cases on which the model is based. The data dependency determines the model success. Hence, it is necessary to invest time and money in data collection and preparation before starting the analysis (Anderson, 2007, pp. 55-59).

The classification of the customer within a credit scoring model is an essential part. A model used for credit decisions often allocates customers into two classification categories: good and bad. A good customer is granted a credit while a customer classified as bad either needs a more detailed manual analysis or is rejected directly (Abdou & Pointon, 2011, p. 10). The classification technique which is relevant for assigning a customer to one of the categories is based on a statistical model. These models can be differentiated in parametric or traditional and non-parametric or advanced techniques. The first-mentioned techniques are defined by making assumptions on the underlying data base. The most used and known techniques are the linear regression, the discriminant analysis (DA) and the logistic regression. The non-parametric techniques do not require any assumptions on the data and include the neural networks (NNs) and the genetic algorithms (Abdou & Pointon, 2011, pp. 13-21) (Anderson, 2007, pp. 57-58). The following paragraphs will provide brief overviews of the five mentioned techniques. It will not provide detailed information of the mathematical background of each of the techniques. The aim is only to deliver an overview of the available and most used techniques and to show the differences between the traditional techniques and the advanced techniques whose importance has increased within the last years due to improved technologies and digitalization. This topic will be further elaborated within the sixth chapter of the thesis.

The linear regression is one of the simplest regression models. The model assumes that with an increase in the independent variable, the response variable changes at a constant rate. The equation for the linear regression is

$$y_i = \beta_0 + \beta_1 x_{1i} + \cdots + \beta_p x_{pi} + \varepsilon_i$$

Equation 1 Linear regression (Anderson, 2007, p. 55)

The linear regression aims to estimate the unknown parameters β. It uses the methodology ordinary least squares. The least square regression line minimizes the sum of the squared residuals which is the difference between the observed value and the fitted value (Chatterjee & Simonoff, 2013, pp. 3-7) (Abdou & Pointon, 2011, p. 14) (Anderson, 2007, pp. 166-169). The advantage of linear regression is its transparency and simplicity. However, the linear regression is based on many assumptions such as linearity or homoscedasticity. As in credit scoring the output is often dichotomous, the linear regression became outdated (Anderson, 2007, p. 167).

The discriminant analysis (DA) is used in two different problem scenarios. The first scenario aims to find a representation of a case providing the best differentiation between groups called the descriptive DA. The second scenario identifies rules to classify cases to the appropriate group called the predictive analysis. Credit scoring focuses on the last-mentioned analysis. The predictive DA identifies characteristics of certain groups and identifies vectors for each group. Further, it compares the sample with unknown group identity with the mean vectors and assigns the sample unit to the group where the distance – called the mahalanobis distance – is the smallest (Tufféry, 2011, pp. 332-338) (Rechner & Christensen, 2012, pp. 309-314). The drawbacks of the DA depend on the statistical method used. Often, a linear DA is used implying the same disadvantages as for the linear regression such as having many assumptions on which the model is based. Moreover, DA is often difficult to understand for the layman. However, for dichotomous variables, it is possible to identify characteristics of a good and a bad customer and to assign the unknown new customer to one of the groups by minimizing the distance between the characteristics. Therefore, it is more suitable in credit scoring than the linear regression (Anderson, 2007, pp. 169-170).

The third parametric and in many literatures described as the most appropriate classification technique is the logistic regression. In general, it is the preferred methodology due to a limited number of assumptions, the usefulness for binary response variables and the simplicity of interpretation for non-statisticians. However, it is a very calculation-intensive technique making it not very popular back in time when computers were not common and the use not widespread (Anderson, 2007, p. 170). The binominal logistic regression "is a procedure for predicting, from a set of independent variables, the log odds that individuals will be in each of two categories of a dichotomous dependent variable." (Treiman, 2014, p. 302).

The logistic regression formula is

$$\ln(\frac{p(Good)}{1-p(Good)}) = b_o + b_1x_1 + b_2x_2 + \cdots + b_kx_k + e$$

Equation 2 Logistic regression (Anderson, 2007, p. 170)

The left side of the equation is the logarithm of the odds and this is linearly related to the predictors. The most often used technique is the Maximum Likelihood Estimation (MLE). The MLE determines the parameters of the model. The values for the parameters are estimated by maximizing the likelihood that the model produces the sample data. It is an iterative approach making it very calculation-intensive (Treiman, 2014, pp. 297-303) (Chatterjee & Simonoff, 2013, pp. 149-157) (Tufféry, 2011, pp. 437-478).

Non-parametric or advanced models do not make any assumptions on the underlying data. There are two models mainly used in credit scoring called the neural networks and the genetic algorithms.

The NNs is "an artificial intelligence problem solving computer program that learns through a training process of trial and error." (Gately, 1996, p. 147). The model is based on the operations of the human brain. The computer program adapts to the environment. Through a training process of repetition of experiences, it can train itself. The result is similar to a decision tree but way more detailed. The NNs technique processes much more data than traditional models. On top of that, it has the ability to train itself to discover relationships and interactions and it does not depend on specific assumptions made about the underlying data base. However, it is impossible to understand the results and the design logic. Therefore, the model is only suitable if it is not necessary to understand the logic behind the decisions made by the model (Anderson, 2007, pp. 174-175) (Abdou & Pointon, 2011, pp. 18-19).

The last worth mentioning technique is the genetic algorithms. The Darwinian survival-of-the-fittest theory is one of the best known evolutionary theories and serves as the basis for the genetic algorithms. "Genetic algorithms aim to reproduce the mechanisms of natural selection, by selecting the rules best adapted to prediction (or classification) and by crossing and mutating them until a sufficiently predictive model is obtained." (Tufféry, 2011, p. 510). The model starts with a few first rules and a predefined objective. The rules are tested by a so called 'fitness' function. The evolution process will always select the best rules which can be detected by maximizing the fitness function. The process will be repeated until no further improvement is possible or until a previously identified number of iterations is reached (Tufféry, 2011, pp. 511-513). The model has the advantage of finding solutions which were not known before. Moreover, many traditional models only lead to one local maximum while the genetic algorithms look for the global maximum. Nevertheless, the process lacks transparency. It needs high computing skills and requirements to lead to a successful and reliable result (Anderson, 2007, pp. 176-177).

The just described statistical techniques used in scoring models all have its advantages and disadvantages. The selection of the technique depends for example on the nature of the data, the objective or the availability of technology and skills. However, machine learning approaches should improve the predictability when used appropriately (Zoldi, 2016).

One possibility to evaluate the credit scoring performance is the classification matrix or so-called confusion matrix. The matrix consists of two rows and two columns reporting the number of cases predicted as good and bad customers and contrasts it to the actual good and bad cases. This allows to identify the so-called type I and type II errors. The type I error represents the good cases classified as a bad credit while the type II error represents the bad cases classified as good. The matrix, however, does not consider the costs associated with the errors. Therefore, another evaluation criterion is the estimated misclassification cost criterion. This is based on the confusion matrix and multiplies the identified percentage of misclassification with the costs. In general, the costs associated with type II error are higher than the type I error costs. Therefore, when selecting the statistical technique, the aim is to minimize the misclassification costs with focus on type II error costs (Abdou & Pointon, 2011, pp. 21-22) (Diekhoff, 1992, p. 306).

3.2. Credit Scoring in Practice

Within the scope of the corporate-wide digital initiative, the Company XYZ rolls out digitalization projects within the entire organization from logistics over manufacturing to central functions. One of the projects is the automation of credit limit decisions. Small customers account for a high percentage of the client base while contributing to only a small part of the overall credit limit exposure. The current process is handled manually with zero percent automation. Once a new or an existing customer places an order, the credit manager receives a credit request. The manager analyzes the customer based on historical payment behavior if available, external and internal ratings and derives the credit limit from the standardized credit limit decision matrix. The credit decision is placed within the SAP system FSCM which dispatches the order. The future process aims at having an automation rate of around 75%. Its decisions, which are based on score predicting future behavior, could enable profitable growth due to fast and adequate credit decisions. Moreover, it leads to less manual efforts by finance and sales leading to the possibility of a higher focus on the more relevant exposure. A more detailed analysis on what automation and digitalization within the treasury department means is provided in chapter 6.

The scoring is based on a machine learning model in R. The response variable in the model is the probability of a customer to become a bad payer in at least one of the next 6 months. The predictors include several internal data such as payment behavior or internal ratings. The output of the model is defined by a binary variable:

$$Y = \begin{cases} 0 & \mathit{if\ the\ customer\ is\ good} \\ 1 & \mathit{if\ the\ customer\ is\ bad} \end{cases}$$

Despite the determination of the binary response variable, the model can also calculate the probability of the customer becoming bad. For this purpose, a cut-off score needs to be defined in order to identify when a customer is bad. The model takes as the refence month December 2015 and uses data of more than 35,000 customers. Based on the input, it predicts whether the customer turns bad within the next six months. The historical data makes it possible to compare the predicted results with the actual results. The model is trained with the input of additional data.

The company has clearly defined rules of the customers being in scope of the automation. Customers can become out of scope in two scenarios. The first scenario is that a customer is directly classified as out-of-scope. A reason for this can be the size of the credit limit or the type of business. Another scenario is that the customer is first in scope but then the model classifies the customer as bad. The further procedure is a manual handling by the credit manager.

Based on the result of the scoring model, the customer gets defined a credit limit. The detailed definition of the credit limit determination rules and the “good/bad”-customer definition cannot be provided due to confidentiality and needs to be taken as given.

The machine learning is still in the testing phase. Several machine learning techniques are assessed. To evaluate the model accuracy and predictability, the confusion matrix is used. This helps to identify the type I and type II error rates as previously explained. The existing model currently has a correctly predicted rate of over 95%. However, especially countries such as South Europe, Middle East and Africa show lower performance compared to North Europe. Additional external data input such as country-level macroeconomic data might be essential to improve the model predictability which is the reason for why the following thesis focuses on the analysis of macroeconomic impact on a customer payment behavior. The output and the “good/bad” customer definition of the model will serve as the basis for the statistical analysis of whether macroeconomic indicators have an impact on the model.

4. Credit Risk Management in different regions

The thesis' focus and analysis are based on the region EMEA – Europe, Middle East and Africa which can be differentiated in 8 broader regions (cf. Figure 4). The eight regions are North-West Europe including United Kingdom, the Benelux countries and the Nordics & Baltics, South-West Europe including France, Switzerland, Iberia and Italy, Central Europe including three sub regions (Europe Central North, West and East), Germany, Russia & CIS countries, Turkey & Azerbaijan, Middle East & Egypt including Mashreq, Iran and Arabian Peninsula and finally Africa including Northwest, West, East and Southern Africa.

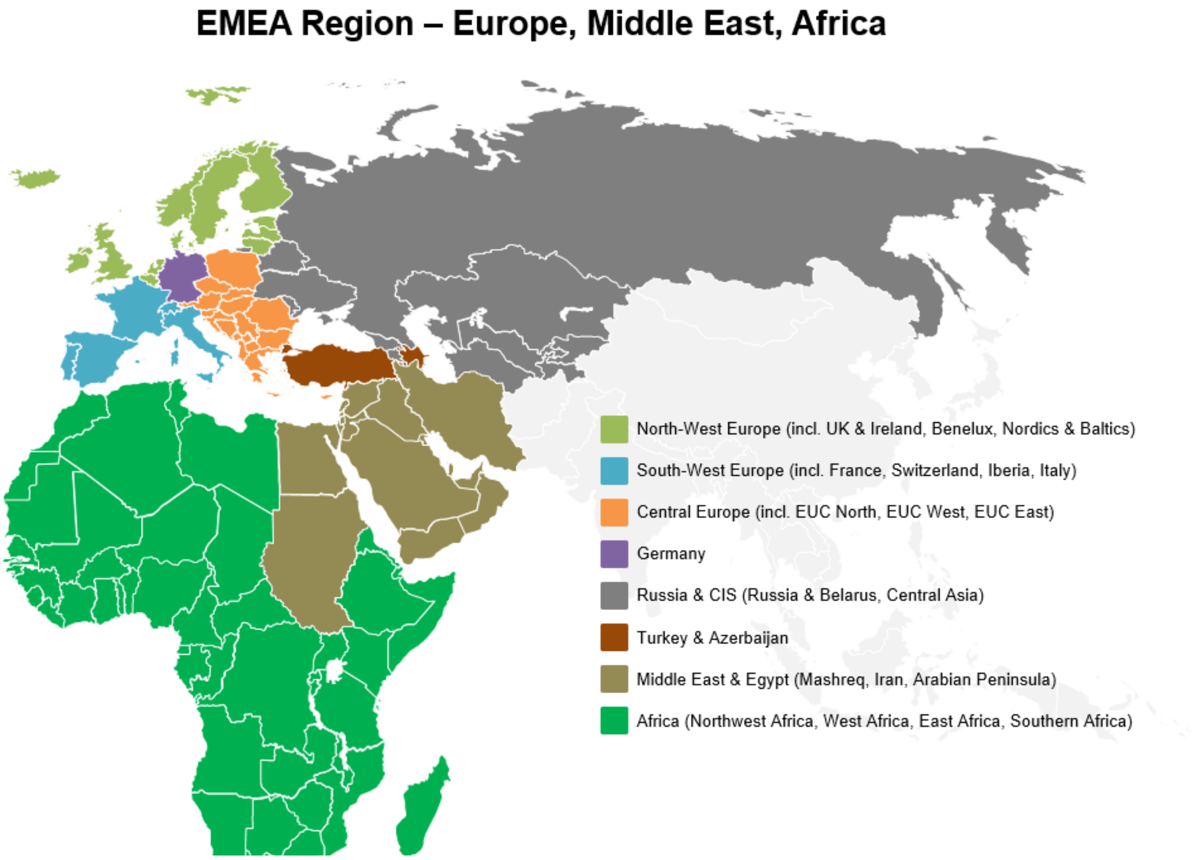
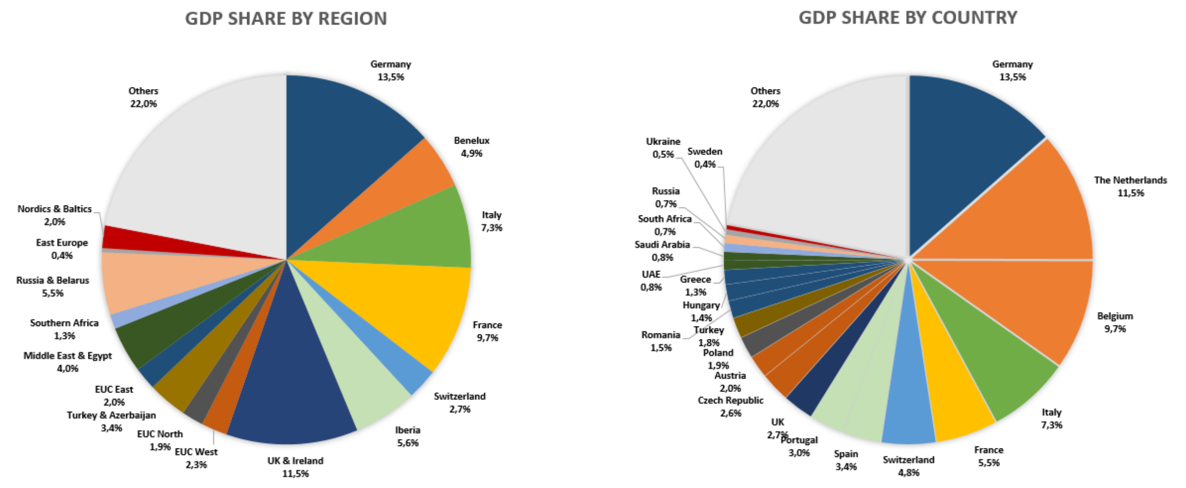


Figure 4 EMEA Region - Europe, Middle East, Africa (created by author)

Summing up all countries being in scope of this region it adds up to 132 countries. Due to this broadness, complexity and variety of countries, the aim was to identify a criterion on which the most relevant countries for the Company XYZ customer portfolio as well as for a region's economy can be identified. Considering the company's portfolio as well as each country's contribution to the regional gross domestic product, it limits the number of countries in scope of the further analysis to 22. These 22 countries account for roughly 80% of the regional gross domestic product. The detailed countries and regions in scope can be seen in Figure 5.



Source: Worldbank

Figure 5 GDP Share per Region and Country (created by author) *(Worldbank, 2015-2016)*

4.1. Differences in Credit Risk Management

Payment behavior and credit risk varies among the different countries within EMEA which can be seen based on the analysis of several key performance indicators such as the Days' Sales Outstanding (DSO), percentage of overdue invoices or a country risk assessment map from credit rating agencies.

The Coface Country Risk Assessment map evaluates the average credit risk by country. The methodology on which the assessment is based takes into consideration three main aspects – financial, political and economic data – supported by expert experience on payment behavior and business climate (Appendix B). The country risk map proves that credit risk varies among regions supporting the assumption that credit risk management needs different focus within different regions. Taking a closer look to the different regions introduced in the previous subchapter, it is possible to provide a general risk level per region. The risk of business defaulting in North-West Europe, Central Europe, South-West Europe and Germany varies from very low to acceptable. In Russia & CIS, Turkey & Azerbaijan, Middle East & Egypt and Africa it is the completely opposite with risk varying from significant to extreme (Coface, 2016).

The difference in credit risk is in addition represented by the DSO (cf. Table 2). It is a measure providing information on how long a company needs to collect the payment after a sale (Investopedia, n.d.). The region with the largest DSO is Turkey & Azerbaijan with 81 followed by Central Europe whose high DSO is mainly influenced by Hungary (DSO: 80) and Greece (DSO: 91). In South-West Europe and Middle East & Egypt it takes 69 and 63 days for a company to receive the cash followed by the best-performing regions Germany and North-West Europe. The surprising region is Africa. A DSO of 47 does not represent the country risk presented in the Coface Country Risk Map (Euler Hermes SA, 2016) (PwC, 2013, p. 53).

Table 2 DSO and Late B2B invoices over 90 days per country (created by author)

DSO and Late B2B invoices over 90 days per country

Country	Region	DSO 2015**	Late Payment over 90 days 2015***	Late Payment over 90 days 2016***
South Africa	Africa	**47**	**7,7%**	**3,1%**
Czech Republic	Central Europe	55	0,7%	0,7%
Austria	Central Europe	44	n.a.	n.a.
Poland	Central Europe	60	14,8%	15,0%
Romania	Central Europe	73	1,8%	20,4%
Hungary	Central Europe	80	0,6%	0,9%
Greece	Central Europe	91	19,9%	7,7%
	CENTRAL EUROPE	**67**	**7,6%**	**8,9%**
Germany	GERMANY	**53**	**0,5%**	**0,2%**
UAE	Middle East & Egypt	62	n.a.	n.a.
Saudi Arabia	Middle East & Egypt	64	n.a.	n.a.
	MIDDLE EAST & EGYPT	**63**	**n.a.**	**n.a.**
The Netherlands	North-West Europe	47	1,2%	0,9%
Belgium	North-West Europe	66	1,3%	1,8%
UK	North-West Europe	51	2,5%	2,6%
Sweden	North-West Europe	52	n.a.	n.a.
	NORTH-WEST EUROPE	**54**	**1,7%**	**1,8%**
Russia	Russia & CIS	56	9,1%	4,4%
Ukraine	Russia & CIS	46*	n.a.	n.a.
	RUSSIA & CIS	**51**	**5,4%**	**3,1%**
Italy	South-West Europe	88	4,4%	3,5%
France	South-West Europe	72	2,4%	2,9%
Switzerland	South-West Europe	48	n.a.	n.a.
Spain	South-West Europe	68	2,6%	3,8%
Portugal	South-West Europe	71	11,7%	9,6%
	SOUTH-WEST EUROPE	**69**	**5,3%**	**5,0%**
Turkey	TURKEY & AZERBAIJAN	**81**	**5,3%**	**5,8%**

* 2013 data
** Source: Euler Hermes, PwC
*** Source: D&B

Another informative figure on the credit risk is the percentage of late payments. Dun & Bradstreet publishes a yearly report on the worldwide payment behavior of B2B transactions. Having a look at the percentage of companies in the different countries with late payments of more than 90 days underlines the differences in payment behavior within Europe, Middle East and Africa. Romania, Poland, and Greece are the worst countries within Central Europe with regards to this indicator. Additionally, these three countries show how significantly late payment behavior can change from one year to the other. In Greece, for example, late payments over 90 days accounted for 20% in 2015 compared to around 8% in 2016. Within the regions Russia & CIS, South-West Europe and Turkey, around 5-10% of all B2B transactions are paid more than 90 days after due date while the amount in regions such as Germany and North-West Europe is of small value (Cribis D&B, 2017) (cf. Table 2).

The main reason for late payments is due to the debtor being in financial difficulties, insufficient availability of funds and formal insolvency of the debtor. The financial difficulties can occur due to either a changing business and economic environment, political changes or bad management practices. These aspects, especially the economic and political situation is therefore taken into consideration from various credit rating agencies when assessing the credit risk of a country or a customer (Intrum Justitia, 2016).

Due to the differences in credit risk among the countries within EMEA, taking into consideration external aspects additionally to the internal information such as historical payment behaviors can improve an assessment's predictability. The following chapters are going to focus on the identification of relevant macroeconomic indicators for a credit risk assessment and the analysis of the impact of such indicators.

4.2. Identification of macroeconomic indicators

Macroeconomic factors make up a part of the overall credit risk assessment. As the macroeconomic environment is a complex science, a first step is the identification of relevant indicators. This identification is based on a three-step approach. First, a literature review identifies a first broad range of categories. The second step is an analysis of different regions within EMEA to get an overview of the business environment and country differences. Based on these two steps, a research is conducted taking into consideration the results of the literature review to test and verify the previously identified indicators, identify the most relevant ones and gain additional input. Another important reason for this three-step approach is that most of the literature is based on credit risk assessment within the banking industry. In general, the credit risk function within a corporation can be seen as the customers' "bank" because they provide credit limits to corporate customers. However, the literature is not solely focused on corporate customers. Therefore, the second and third steps within the identification process provide the possibility to identify the most relevant indicators for corporate customers.

4.2.1. Literature review on macroeconomic indicators in credit assessment

The previous chapters pointed out the importance of qualitative as well as quantitative aspects within the assessment of the customer's creditworthiness. In general, credit models take into consideration company-related variables as well as systematic economic indicators. These indicators are called credit drivers as they influence credit risk (Iscoe, Kreinin, Mausser, & Romanco, 2012). Mileris (2012) identified in his research a "significant dependency between macroeconomic determinants of a country and the loan portfolio credit risk in banks" (Mileris, 2012, p. 502) . This study focused on the macroeconomic indicators identified by Figlewski, Frydman and Liang (2007). It elaborates the change in corporate credit risk due to changes in economic conditions. This credit rating took into consideration firm-specific indicators with focus on the firm's historical performance as well as several macroeconomic indicators. The statistically significant macroeconomic indicators could be grouped in three major categories: The *General Macroeconomic Conditions*, describing the overall health of the economy, the *Direction of the Economy* indicators identifying whether there is an improvement or a worsening of the economy and the *Financial Market Conditions* providing a picture of the overall financial market situation. The General Macroeconomic Conditions include indicators such as unemployment, inflation, capacity utilization, gross domestic product (GDP) and industrial production. The Direction of The Economy category comprises the growth rates and changes of unemployment, GDP or industrial production. Interest rates, stock market indicators as well as foreign exchange rates are included within the last category (Figlewski, Frydman, & Liang, 2007, pp. 9-13). A more detailed description of the macroeconomic indicators will be provided when describing the variables used within the statistical analysis.

Jakubík (2007) identified similar indicators as already mentioned. Within his study, he identified a significant relevance of interest rate, inflation and GDP. A change in GDP influences the credit risk as it can negatively influence corporate earnings, wage and unemployment rate. This again impacts the loan quality. If the interest rate rose, it would increase the corporate financing impacting the credit risk negatively (Jakubík, 2007, p. 71). Jakubík emphasized the importance of being interested in the relationship of credit default and the economic situation. Credit managers need to gain knowledge of potential increase in credit risk due to changes in the economic environment. As macroeconomic indicators provide an outlook on the economy's direction, it is possible to use them for future payment behavior predictions which is the aim of every scoring model (Jakubík, 2007, p. 61).

An additional paper often cited within the context of the impact of macroeconomic information on the predictability of credit default is based on similar indicators as already mentioned. The analyzed data set included interest rates, industrial production, stock market indices, GDP, unemployment rate as well as consumer price indices (CPI). However, as statistically significant were identified unemployment rate, Dow Jones Index and the industrial production (Hamerle, Dartsch, Jobst, & Plank, 2011, pp. 9-12).

All the just mentioned papers did not differentiate between several countries. However, Beck, Jakubík and Piloiu (2015) point out the following: "The fact that loan performance is tightly linked to economic cycle is well known and not surprising. Yet the deterioration of loan performance was very uneven across countries." (Beck, Jakubík, & Piloiu, 2015). They analyzed correlations between macroeconomic indicators and non-performing loans in 75 countries. In general, they identified GDP growth, share prices, exchange and interest rates as the most important indicators. However, the dependency varied within the countries. Share price was especially important for companies with an important and large stock market while the exchange rate was important for customers in countries with pegged exchange rates (Beck, Jakubík, & Piloiu, 2015, p. 546). As this thesis also focuses on the differences within the EMEA region, this aspect will be kept as an assumption which will be further analyzed within the statistical analysis.

In addition to the theoretical studies, the author took into consideration a practical example. S&P Global developed a credit risk scenario analysis feature within its Capital IQ tool which applies macroeconomic scenarios to credit risk assessments. This tool is used by corporations to analyze the effects of economic changes on the customer's performance. This model is built on macroeconomic variables including real GDP growth, industry specific indicators, unemployment rate, oil price, interest rates, bond yields and stock indices (S&P Global Market Intelligence, 2018, p. 5) (S&P Global Market Intelligence, n.d.).

Many studies have proved a significant correlation between macroeconomic aspects and the credit default or the customer's creditworthiness and emphasized different sensitivities to economic changes among different countries. This supports the assumption to include macroeconomic aspects within a credit scoring model to improve the predictability of especially economically difficult countries and provides a broad set of relevant macroeconomic indicators. However, since many studies focused on the banking industry (but not solely on individual but also corporate customers), the following two steps will focus especially on the corporate environment to identify the most relevant set of indicators which will be used for the statistical testing.

4.2.2. Comparison of different regions within EMEA

The second step in the identification of relevant macroeconomic indicators for a credit risk assessment is the analysis of the region's economies. A region's or country's dependency on a commodity price or export can significantly influence the overall economic situation if these factors change.

The following paragraphs are going to focus on the overall economic situation of the different regions within Europe to get an overview on the most important drivers. Additionally, this analysis allows to make assumptions on whose regions' payment behavior or credit risk might be more volatile to changes in economic situations. Most of the regions' economies are dependent on the same economic indicators, however to a different extent.

<u>Germany:</u>

Germany is known as a leading exporter of cars, machinery, household products and chemicals. Due to the country's maturity, domestic demand is one of the main drivers of growth for the next years supported by exports. Exports account for 46 % of GDP in 2016 (cf. Appendix C). However, due to the political issues with regards to the current Ukrainian and Russian crisis, sanctions lead to a decrease in exports. Germany is Russia's most important European trading partner. Nevertheless, a skilled labor force, a low unemployment rate (4.1% in 2016, cf. Appendix C) and strong domestic consumption supports Germany's economic growth (Central Intelligence Agency, 2018a) (Passport Euromonitor, 2018a) (Atradius, 2017a, pp. 11-12) (FocusEconomics, 2018a).

North-West Europe

The Benelux region's economy is highly influenced by external demand. Exports account for 82% of GDP for both countries, Belgium and the Netherlands (cf. Appendix D). Being an export-driven economy implies being vulnerable to external shocks. Therefore, the Benelux region can be highly influenced by inflation and global demand. Hence, the region has a well-diversified economy spreading the risk among different industry sectors. UK is a strong export partner for both countries implying that decisions with regards to Brexit can affect their economies (Central Intelligence Agency, 2018b) (Central Intelligence Agency, 2018c) (Passport Euromonitor, 2018b) (Passport Euromonitor, 2018c) (Atradius, 2017a, pp. 5-6;17-18).

On the example of United Kingdom, the impact of political decisions and a change of economic situation can be seen. Brexit led to an economic slowdown after being announced. On top of that, UK's most important industry is services, especially banking, insurance and business services. As this is the main driver of GDP, the economy was hit by the financial crisis showing the importance of the financial sector. Inflation as well as the uncertainty associated with Brexit led to decreasing household spending in 2016 (Central Intelligence Agency, 2018d) (Passport Euromonitor, 2018d) (Atradius, 2017a, pp. 25-26).

Sweden, representative for the Nordics & Baltics, is a competitive industry with a high living standard. Sweden is characterized by a decreasing unemployment rate (cf. Appendix D). Its economy is mainly driven by investments, exports and private consumption (Central Intelligence Agency, 2018e) (Passport Euromonitor, 2018e) (Atradius, 2017a, pp. 21-22).

South-West Europe

The most important countries of South-West Europe identified previously are Italy, Spain and Portugal, France and Switzerland.

Italy, Spain and Portugal have high unemployment rates due to recent economic recessions (cf. Appendix E). The worsening work situation impacts domestic demand decelerating economic growth of a country. However, the low interest rates in Europe work against the negative shift. On top of that, the countries are impacted by positive export growth in 2015 with a slight decrease in 2016 due to increasing competition from Eastern Europe and Asia. This is an example of how different economic effects level out. Although domestic demand would decrease economic growth, a good financial and export market situation work against the negative effects (cf. Appendix E) (Central Intelligence Agency, 2018f) (Central Intelligence Agency, 2018g) (Central Intelligence Agency, 2018h) (Passport Euromonitor, 2018f) (Passport Euromonitor, 2018g) (Passport Euromonitor, 2018h) (Atradius, 2017a, pp. 15-16;19-20).

Compared to other European mature countries, France still suffers from a high unemployment rate (10 % in 2016, cf. Appendix E). This have impacted the consumer demand within the last years. In general, economic growth in France is also mainly driven by domestic and external demand (Central Intelligence Agency, 2018i) (Passport Euromonitor, 2018i) (Atradius, 2017a, pp. 9-10) (FocusEconomics, 2018a).

The last country to consider for South-West Europe is Switzerland. Switzerland is a modern economy with a low unemployment rate of 4.9% in 2016 (cf. Appendix E). The most important industry for the country is the financial sector which makes is very vulnerable to changes in capital markets and financial markets. In 2015, the central bank cut the peg between the Swiss franc and the Euro. This hit the economy. Exports decreased due to the sharp appreciation. Switzerland heavily relies on exports. Around 77% pf GDP derives from exports. Therefore, such a change in exchange rate can influence a country's economy sharply. Nevertheless, the economy recovered quickly due to the strong domestic demand (Central Intelligence Agency, 2018j) (Passport Euromonitor, 2018j) (Atradius, 2017a, pp. 23-24).

Central Europe

The Central European economy is dominated by the countries Austria, Poland, Romania, Hungary, Greece and the Czech Republic.

Austria is characterized by a well-diversified economy mostly driven by domestic consumption and exports accounting for around 51% of GDP in 2016 (cf. Appendix C). However, due to the economic diversity, the exports are not as much dependent on external shocks within one industry (Central Intelligence Agency, 2018k) (Passport Euromonitor, 2018k) (Atradius, 2017a, pp. 3-4).

Contrasting to this are the Czech Republic, Romania, Poland and Hungary. These countries are very vulnerable to external shocks because of their dependency on exports. Around 80% of the Czech Republic's GDP is made up of exports. Due to the high dependency on the vehicle industry and on the European industry, situations such as the Brexit would impact the economic situation in the country significantly. Nevertheless, the Czech Republic belongs to one of the strongest economies in

Europe and apart from the exports, the economic growth is supported by private consumption mainly driven by the low unemployment rate (Central Intelligence Agency, 2018l) (Passport Euromonitor, 2018l). Romania has compared to other European countries a smaller dependency on exports (41% of GDP in 2016, cf. Appendix C), however, it is also heavily dependent on the European Union. Therefore, the country is vulnerable to external shocks and changes within the EU. Further, economic growth is supported by domestic growth due to decreasing unemployment and a growth in GDP (Central Intelligence Agency, 2018m) (Passport Euromonitor, 2018m). Poland is similar to Romania (Exports are 52% of GDP in 2016, cf. Appendix C). The only difference is that the country exports 80% to non-EU partners. Crisis such as the one between Russia and Ukraine affects the economy negatively (Central Intelligence Agency, 2018n) (Passport Euromonitor, 2018n). Hungary is even more dependent on exports as it accounts for around 90% of the GDP in 2016 (cf. Appendix C). Therefore, exports are a main driver of economic growth. Changes in the trade partner's economies impact Hungary directly (Central Intelligence Agency, 2018o) (Passport Euromonitor, 2018o) (Atradius, 2017b, pp. 6-7;8-9;10-11;13-14) (FocusEconomics, 2018b).

The last country taken into consideration in the country cluster Central Europe is Greece. Greece went into a deep recession after 2009. In 2014, the economy began to recover. However, the country still suffers from non-performing loans and ongoing political uncertainty which directly influences the private consumption (Central Intelligence Agency, 2018p) (Passport Euromonitor, 2018p).

Russia & CIS

Russia and Ukraine are the two countries with the highest GDP share in the region Russia and the Commonwealth of Independent States. This region's economic development coheres with the world commodity prices. Higher commodity prices lead to a positive economic development. Moreover, the markets are vulnerable to the global financial markets. Lower commodity prices, currency depreciations and increase in interest rates impact the economic development (FocusEconomics, 2018c).

Russia is known as one of the world's largest oil producer and a leading exporter of metals such as aluminum explaining the country's dependency on the world commodity prices. The recession in 2015 and 2016 showed the impact of changing market conditions on the Russian economy. Falling oil prices and political sanctions led to a strong economic decline. Compared to the before mentioned regions, Russia is not heavily dependent on exports as it contributes to the GDP with 25% (cf. Appendix F). However, the country experienced a decrease within the last years due to sanctions by the US and EU (Central Intelligence Agency, 2018q) (Passport Euromonitor, 2018q).

Ukraine is a country known for the possession of minerals being the world's largest supplier of titanium and possesses much iron ore. Apart from the dependency on the mineral's world prices, the country's main driver of economic growth is the domestic demand. However, due to the difficult political situation with Russia, the economy slows down (Central Intelligence Agency, 2018r) (Passport Euromonitor, 2018r).

Turkey & Azerbaijan

Turkey's economy is mainly influenced by the rising unemployment and high inflation. Although the country has a good financial market and banking system, the high inflation affects the economy and leads to an economic slowdown. The political situation, especially the failed coup attempt worsened the overall situation (cf. Appendix F) (Central Intelligence Agency, 2018s) (Passport Euromonitor, 2018s) (FocusEconomics, 2018) (Atradius, 2017b, pp. 20-21).

Middle East & Egypt

Saudi Arabia and United Arab Emirates (UAE) are the two relevant countries within the region Middle East & Egypt. Both countries face the same challenges. The main economic driver within the countries is the oil price. They possess huge oil reserves and their economies suffered in 2015 due to the sharp decrease in oil prices. Due to the economic dependency on the oil price, the governments in both countries started diversification programs of the economy. Additionally, both countries suffer from a high unemployment rate within the last years (cf. Appendix G). UAE's economy highly depends on exports, mainly driven by oil exports. Exports contributed to 103% of GDP in 2016 (cf. Appendix G) (Central Intelligence Agency, 2018t) (Central Intelligence Agency, 2018u) (Passport Euromonitor, 2018t) (Passport Euromonitor, 2018u) (Atradius, 2017c, pp. 11-12;16-17) (FocusEconomics, 2018c).

Africa

South Africa's economic growth is influenced by several factors. The country has a high unemployment rate of around 27% in 2016 with an increasing trend over the last years (cf. Appendix G). This directly impacts the consumer spending again impacting economic growth. Moreover, South Africa is an economy with a significant amount of natural resources and the largest stock exchange market within the African area. This makes the country vulnerable to external shocks. Inequality, poverty and unemployment are the main challenges within the country affecting significantly the economic growth (Central Intelligence Agency, 2018v) (Passport Euromonitor, 2018v).

Considering all country snapshots, one can summarize the main drivers of economic growth. Especially within one region, the drivers are similar but it depends on the country's economy, maturity and openness which drivers mainly impact growth. However, private consumption, unemployment rate, financial market indicators, export and commodity prices are the most listed driver significantly impacting an economic situation. Apart from that, due to the difficult political situation such as the Russia and Ukraine crisis or the Brexit decision, one can see the impact of governmental decisions which are often the source of macroeconomic changes.

4.2.4. Survey with Credit risk management community

A survey on the topic of macroeconomic information within a customer credit risk assessment aims to identify the relevance seen by credit managers and at evaluating the most relevant indicators. Therefore, the author conducted a survey within the Company XYZ with a sample population of 17 credit managers as well as an external survey with a much larger sample size of 132 respondents (Appendix H). The following chapter first outlines the survey design followed by a description and interpretation of the findings.

According to Saris and Gallhofer (2014), an eight-step approach needs to be taken into consideration when designing a survey (cf. Figure 6). The author will follow this approach when elaborating the methodology of survey design and survey execution. (Saris & Gallhofer, 2014, pp. 4-10).

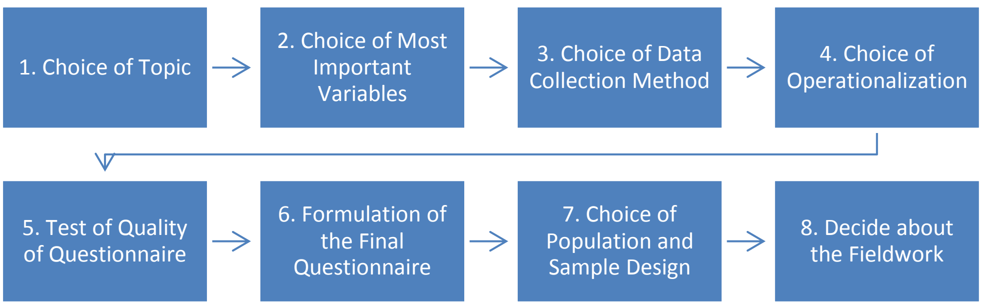


Figure 6 The 8-step approach for survey design (created by author) (Saris & Gallhofer, 2014, pp. 4-10)

1. Choice of topic

Taking into consideration the overall scope of the thesis, the survey research objective is to elaborate on two aspects regarding macroeconomic indicators in customer credit risk assessment: firstly, the survey analyses the importance of macroeconomic indicators in a corporate credit risk analysis in general. Secondly, it aims to elaborate which macroeconomic indicators are important when assessing the customer's creditworthiness within Company XYZ, especially with regards to the specific business of the corporation.

2. Choice of the most important variables

The second step within the survey design is to identify the variables to be measured. When referring to the two aims identified before, the choice is rather obvious. However, as the field of macroeconomics and the related indicators are endless, the previous literature review (cf. subchapter 3.2.)) helped to identify relevant indicators for scoring models which are analyzed within the survey. The survey focuses on the three broad categories: General Macroeconomic Conditions, Direction of the Economy and Financial Market Conditions. One limitation, as already mentioned earlier, is that the literature mostly elaborated the credit risk scoring of customers within the banking industry as they are far more developed as credit risk departments within corporations. This limitation will be taken into consideration within the design of the answer choices which will be explained in the following.

3. Choice of Data Collection Method:

The data collection method determines how the respondents are surveyed. There are various possibilities from personal interviews to mail survey to telephone interviews. The author decided to conduct an online survey due to several reasons. The survey covers a topic which is not everyone’s routine work. Some questions might need some more consideration. Sending out the survey to the respondents enables them to have more time to think about the questions. Personal or phone interviews could lead to hasty responses. This justification goes in hand with the second argument. The survey will be sent out to different cultures, including low-context culture who feel more comfortable with having more time to respond. The types of questions are more feasible for answering it by the respondents themselves as well (Diem, 2002).

4. Choice of Operationalization

Operationalization can be set equal to the translation of the concepts into questions which is one of the most challenging tasks within the survey design. One question can be understood completely different from various people. On top of that, choice of operationalization was one of the most focused topics within the survey design as the survey is sent out to credit managers from various cultural backgrounds which stresses the importance of appropriate formulation. This operationalization takes into consideration the formulation of the questions, the response categories given and whether additional text for introduction, additional information, definitions or instructions is provided (Saris & Gallhofer, 2014, pp. 6-8).

As discussed earlier, the formulation of the questions is based on the literature review of macroeconomic indicators in scoring models. However, many of these scoring models are based on the banking industry. Therefore, the survey is built as a half-open question type interview. As the field of macroeconomics is enormous and endless, is it necessary to provide a selection of indicators. However, as the respondents are experts in the field of customer analysis, the questions always provide an option to deliver further comments, information and own thoughts/expertise on the topic. Therefore, some questions are made as an open request while others provide possible responses (Saris & Gallhofer, 2014, p. 99).

Regarding the closed categorical requests, attention was paid especially to the completeness of the answer choices provided. For some questions, the completeness was also ensured by adding the possibility of an open answer category.

When assessing the importance of macroeconomic indicators within a credit assessment, an ordinal scale was chosen. Questions asking about the importance of a topic and providing an ordinal scale as an answer possibility always implies a certain subjectivity (cf. Questions 3 & 4 in the survey). However, this is unavoidable because with further introduction and definition of the work “importance”, the author would have set a direction (Porst, 2014, p. 73.75).

Regarding the number of categories given, literature provides many different possibilities. However, most of the literature agrees that a 5- to 7-point scale is optimal (Porst, 2014, pp. 83-88) (Saris & Gallhofer, 2014, pp. 111-112). Another discussable issue is whether to provide an equal or unequal scale. With an unequal scale, one might have the danger of offering a category in the middle which many respondents select as they cannot or do not want to decide for one direction. However, offering an equal scale might have the danger to force to decide for one position even if the respondents really have a middle tendency (Iarossi, 2006, pp. 59-63). The author decided to use an unequal scale within the questionnaire. Most of the respondents are experts and it would be also valuable to get to know whether they are in fact indifferent to the topic of macroeconomic indicators in a credit risk assessment. The author does not want to force them to decide for one direction because the middle possibility provides valuable insights as well (Porst, 2014, pp. 83-84). Literature also argues about the importance of adding the answer choice “I don’t know”. The “I don’t know” answer choice has several obstacles. Respondents might choose the option because of several reasons which have nothing to do with whether they know the answer or not. Reasons can be that the respondents do not want to be asked further or they do not want to think about the question and therefore choose the easiest answer choice. This is called the “satisficing behavior of a respondent” (Saris & Gallhofer, 2014, p. 107). On top of that, if many people choose the answer choice “I don’t know”, fewer people are left for the analysis and elaboration of the question. Therefore, the author has conducted the so called “don’t know” check and decided not to include the answer possibility because of two reasons: First, the survey is conducted with experts performing credit risk assessments on a daily basis. It is assumed that they can assess the importance of indicators. Second, the questions ask about an opinion and not a fact. Therefore, it should be possible to provide an appropriate answer which will not distort the results (Saris & Gallhofer, 2014, pp. 106-107).

For the questions related to the specific macroeconomic indicators (cf. Questions 6-10), three approaches are used. First of all, indicators found in the literature review are listed to provide an idea on what is meant by the specific categories. Second, it is asked to select the relevant indicators and to rank them. This provides not only an overview on what indicators are seen as important but also ranks the indicators with regards to the importance. This ranking is an important basis for the further analysis whether to include the indicators within the scoring model or not. Third, it is always given the opportunity to add additional indicators to make use of the respondents’ expert knowledge and to ensure to not restrict them. Some of the questions needed to be adjusted for the external survey due to technical design issues with SurveyMonkey.

When necessary, the author provides informative additional instructions as some questions need to be answered with regards to the respondents working procedures and some with regards to their expert experience and knowledge. However, this is kept to a minimum to not influence the respondent (Saris & Gallhofer, 2014, pp. 115-118).

5. The Test of the Quality of the Questionnaire

In order to test the designed survey, the author conducted two pilot studies. The first pilot was conducted with a credit analyst being responsible for the customer assessment of global customers and the second pilot was conducted with the head of credit risk management of the region Europe, Middle East and Egypt. After both pilots, the survey was adjusted according to both, content and survey design.

On top of that, based on the drawbacks identified after the internal survey was conducted, the external survey was adjusted to avoid misunderstandings which appeared within the survey with the internal colleagues.

6. Formulation of the final questionnaire

After all corrections being made, the final version was tested and discussed again before it was sent out to the relevant sample population. Moreover, the final layout of the questionnaire was discussed. For coding and interpretation of the survey, Microsoft Word and Excel as well as SurveyMonkey were used.

7. Choice of Population and Sample design & 8. Decide about the Fieldwork

As mentioned earlier, the author conducted a company-internal survey as well as an external one. The two sample populations will be explained in the following.

The internal survey aimed at interviewing the local credit risk management. CRM at Company XYZ has a global office at the headquarter handling global customers, the systems and governance as well as regional offices with credit managers being responsible for the credit risk management within their country cluster. This ensures more local knowledge and possible personal relationships enabling a good overview of the customer portfolio. The sample of the internal survey was therefore set up with the head of credit analysis of each of the regions, making a total population of 17 respondents. This ensured getting feedback from each region within EMEA.

The external survey was conducted in cooperation with FCIB Global. FCIB is a global association of executives in Finance, Credit and International business. The association consists of global credit and trade finance professionals of companies of all size in more than 76 countries. The survey together with FCIB enabled to base the observation on a larger sample size as well as receiving answers from different companies to elaborate whether the issue of macroeconomic indicators is a current topic even outside Company XYZ. The external survey with FCIB finally led to 132 respondents from 20 different industries and 19 different countries. As this is a global association, the survey was run globally (cf. Appendix I).

The following survey result description and analysis will follow the same order as the questions in the questionnaire. Moreover, it will directly compare the results from the internal with the results from the external survey.

The first part of the survey aimed at identifying the importance and the overall consideration of macroeconomic indicators within a corporate credit risk assessment. Considering the importance of macroeconomic indicators within a credit risk assessment, the credit managers of both surveys clearly state a tendency of importance however being very centered. Internally, 53% consider macroeconomic indicators as important and 23% even as very important. None of the internal credit managers value it as unimportant or even very unimportant. Externally, the importance is worldwide ranked a 5 out of 10 while in Europe it is a 6 out of 10. Within Europe, especially managers from the northern countries consider the indicators as an important part of the credit assessment (cf. Figure 7).

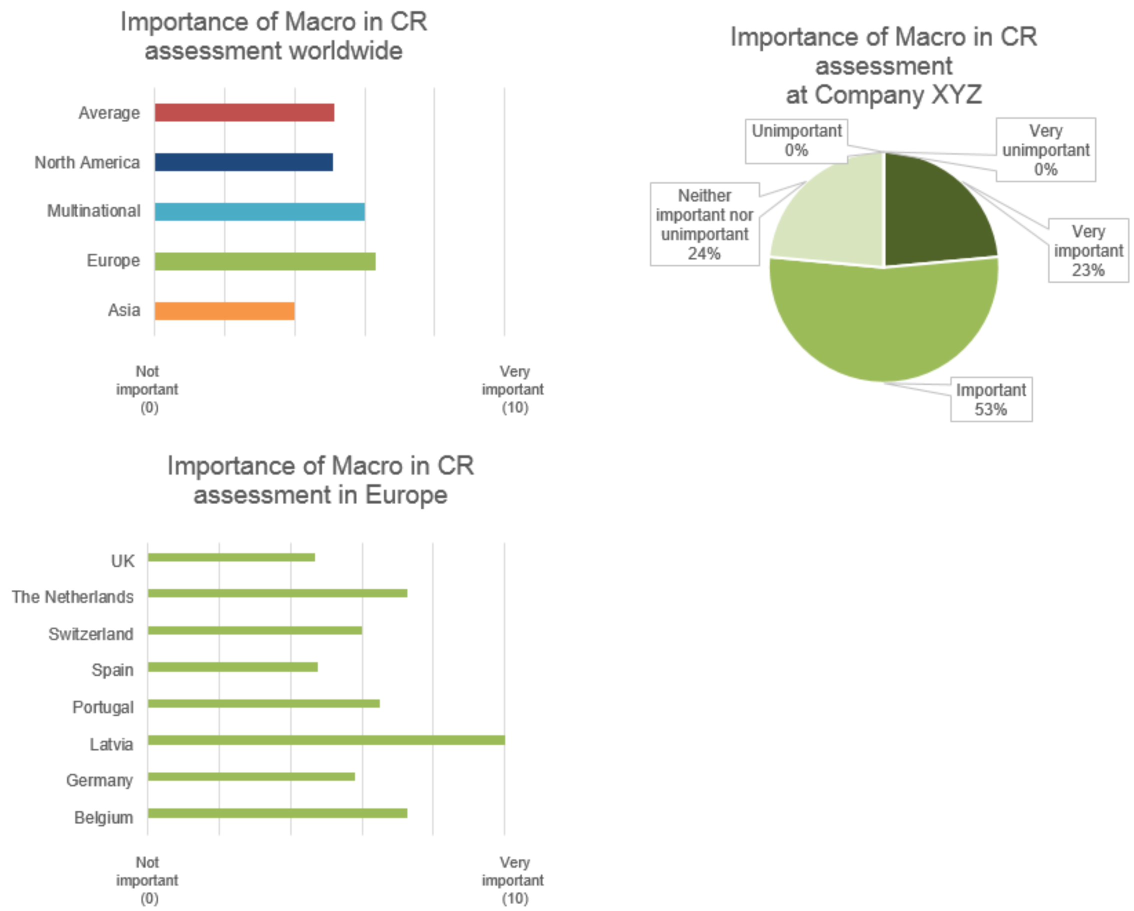


Figure 7 Importance of Macro in Credit Risk assessment (created by author)

The next question asked about the current consideration of macroeconomic indicators as a percentage of the overall assessment. Internally, 53% of the respondents' report that macroeconomic indicators make up about 5-10% of the overall assessment. The results recorded externally are very spread. 26% reported less than 5%, 17% reported 5-10%, 25% 11-20% and 27% 21-50%. This shows that the topic is handled differently within corporations. While at Company XYZ, it takes around 5-10% of the overall assessment, the consideration in other companies is different. Nevertheless, worldwide, almost 90% of the respondents stated that they include always or occasionally macroeconomic indicators within their credit decisions emphasizing the importance of macro data within an assessment spread over all industries and countries. In Europe, the percentage is even higher. 96% of all corporations take macroeconomic indicators into considerations regularly or occasionally when assessing a customer (cf. Figure 8).

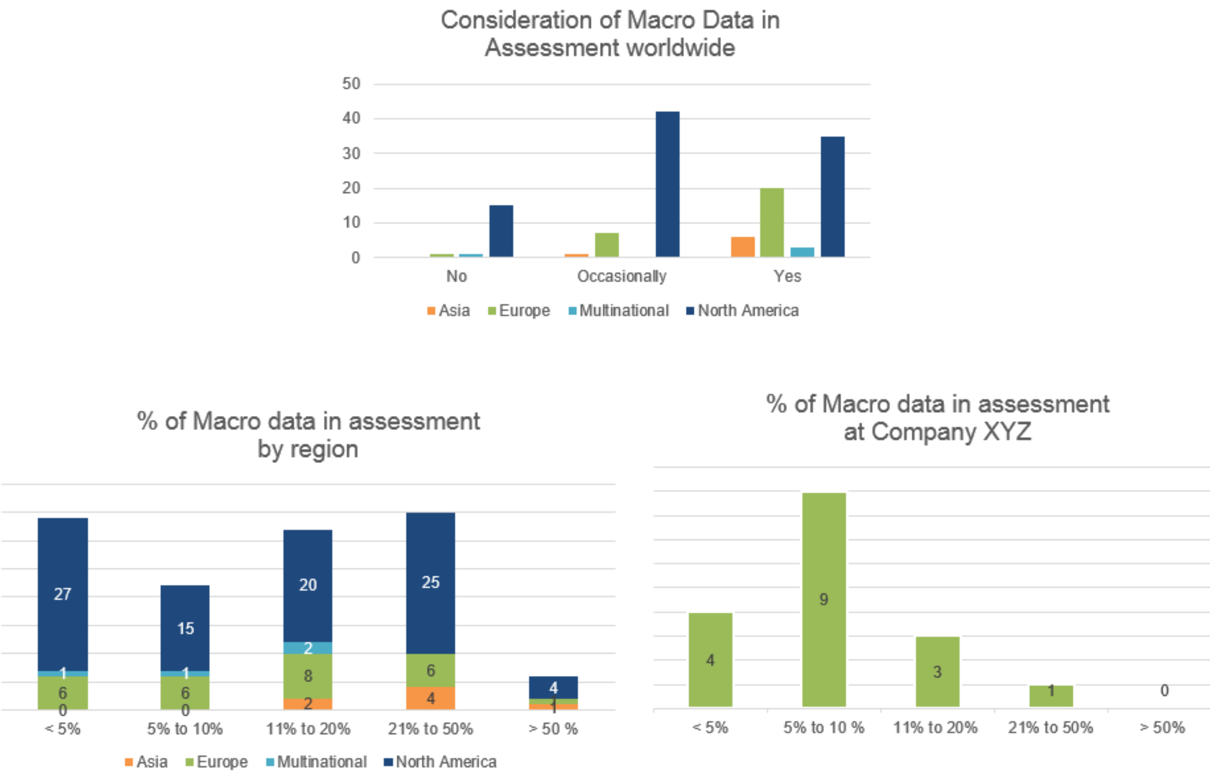


Figure 8 Consideration of macro data is credit assessment (created by author)

The second part of the survey had the objective of analyzing and identifying the most relevant indicators which credit managers see as important to consider when analyzing a customer's creditworthiness.

Three basic categories were provided with the question to rank them according to their importance. Internally, the category identified as most important was the direction of the economy, followed by the financial market indicators and the general macroeconomic indicators. Externally, the respondents worldwide identified the identical order. In Europe, the first two categories changed order, identifying the financial market indicators as the most important. Keeping this in mind, the indicators belonging to the direction of the economy and the financial market category should be placed special focus on when including indicators in the predictive model (cf. Figure 9).

Figure 9 Ranking of categories of macro indicators (created by author)

The three following questions dove into each of the previously mentioned categories to identify specific measures. The list of indicators provided for the general macroeconomic conditions was the longest. The credit managers within Company XYZ identified inflation, real GDP, consumption indicators and export and import indicators as the most important. When assessing the top 3 indicators chosen by each region externally, it is possible to minimize the list to seven indicators including GDP, industrial production, the corporate insolvency rate, inflation, consumption indicators, unemployment rate and export and import indicators. This shows an overlap of the two surveys. All the indicators mentioned internally were also identified by the respondents of the external survey. Summarizing the results of the category identified as most important – the direction of the economy – the real GDP growth was ranked as the most important factor. Lastly, the third category shows an overlap in the identification of the most important categories: the interest rate and the exchange rates. These two factors seem to be important with regards to credit risk (cf. Figures 10, 11 & 12).

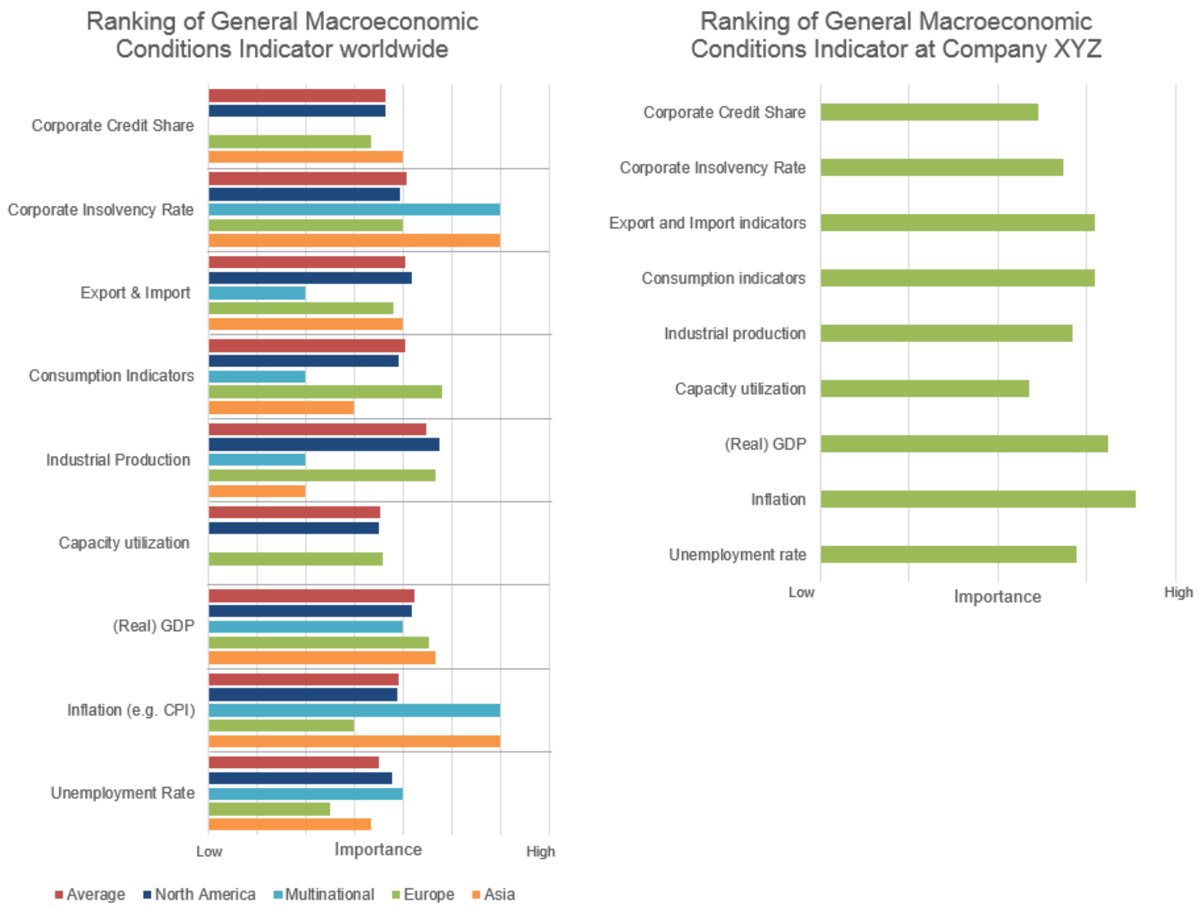


Figure 10 Ranking of General Macroeconomic Conditions Indicator (created by author)

Apart from the three categories provided within the survey, another question asked to identify additional indicators or indicators which the experts see as important especially for their country or industry. A clear trend towards the indicators oil/gas price and commodity prices was observable. This was mentioned by 30 of all respondents. On top of that, a factor often mentioned was the political situation or political decisions being often the trigger point for economic changes.

Due to the fact that the external survey was conducted together with FCIB, the organization's aim was to identify whether credit managers see a lack of knowledge in their skillset when considering macroeconomic indicators within their assessment. The results show that 56% of all respondents think that the co-workers do not have the relevant skills to consider macroeconomic indicators/effects when making a credit risk assessment. This shows that credit managers, although identified as experts within the credit risk assessment, might not have the relevant skills to include macroeconomic effects within their analysis.

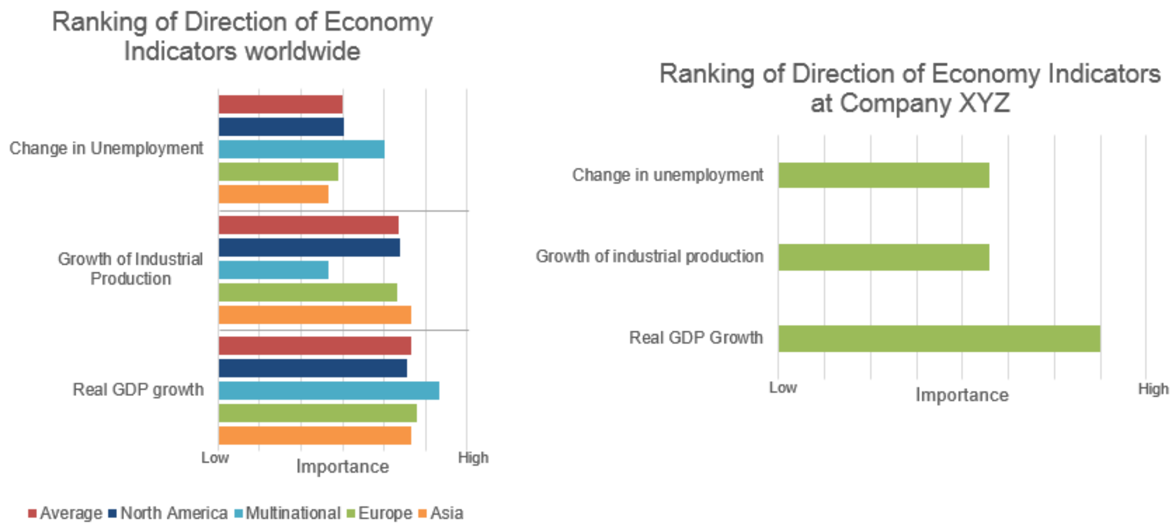


Figure 11 Ranking of Direction of Economy Indicators (created by author)

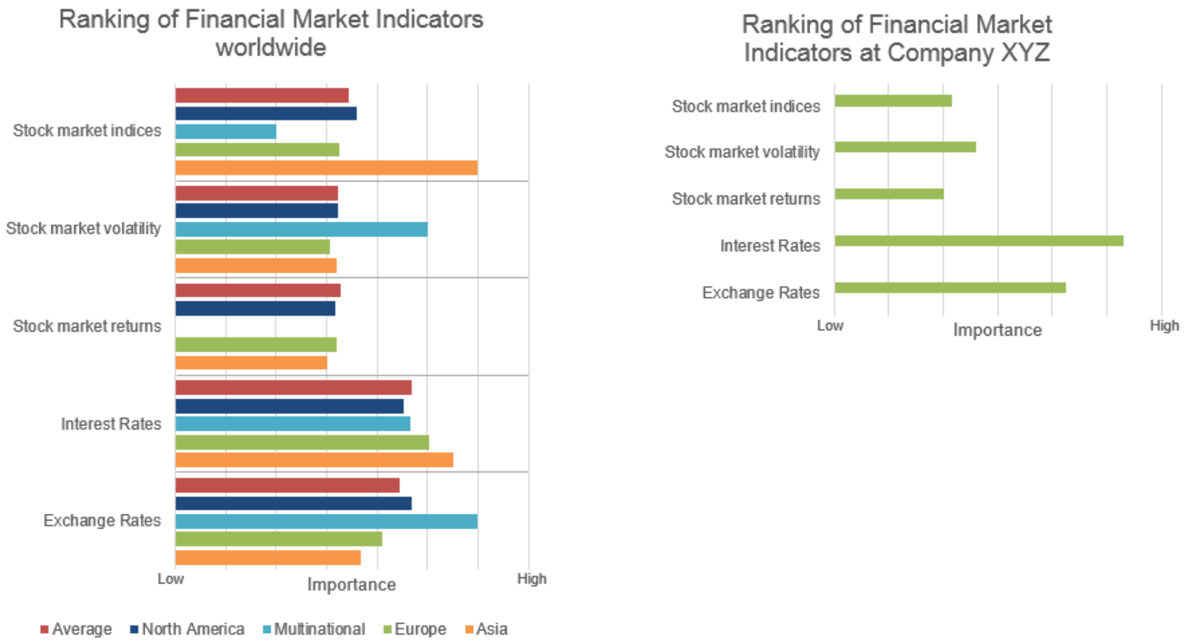


Figure 12 Ranking of Financial Market Indicators (created by author)

Summarizing the results, macroeconomic indicators within a credit risk assessment is evaluated as important or even very important across several industries and countries. The internal as well as the external survey both showed the same direction of importance. However, the percentage of consideration within a credit risk assessment shows a wide range from less than 5% to around 50%. Additionally, both surveys identified indicators for each of the categories provided. A summary can be seen in Chapter 7.1 in Table 4. The results of the survey serve as a basis for the statistical analysis.

Even though the author has conducted a detailed survey design process, it is possible to identify a few drawbacks and limitations which need to be taken in mind.

One question type within the survey aimed at identifying the relevant indicators within the three provided categories and to rank them according to their importance. Some of the respondents internally, chose all the indicators and ranked them from one to nine while others only chose two. This complicated the evaluation. Therefore, the question type was changed for the external survey limiting the number of possible choices to three in total.

A second aspect worth mentioning here with regards to survey design is the fact that the author provided a list of indicators. This might have led to the result that the respondents have relied on the list provided and have not thought about additional indicators which might have been important although given the opportunity to add further. However, the author decided to provide a list of indicators based on the literature review due to the complexity of the macroeconomic environment. Nevertheless, this might have led to the exclusion of important indicators. Especially in the category identified as most important namely the Direction of the Economy, no additional indicators were mentioned.

Another drawback within the internal survey was the small sample size. It showed a clear trend for the company. However, as it was only one response for each country cluster, it was difficult to identify country differences due to the small sample. Nevertheless, it needs to be taken in mind that the result per country is from an expert assessing customers daily.

The last worth-mentioning drawback is the limited influence on the sample population for the external survey. As the external survey was conducted in cooperation with FCIB, it was impossible to have an impact on the countries responding. Therefore, the results are controlled by credit managers from the United States while credit managers of countries such as Middle East or Africa have not responded. In total, more than 3,200 emails were sent out with a response rate of around 4%.

5. Impact of macroeconomic indicators on credit risk assessment

The survey conducted revealed the relevance of macroeconomic indicators from the credit managers' perspective. Moreover, it aimed to identify which indicators should be considered within a customer assessment. The results serve as a basis for the statistical analysis. The objective of the statistical analysis is to identify whether there exists a correlation between the macroeconomic indicators and the payment behavior of the customer to evaluate whether the consideration of these factors will lead to a better model predictability. The analysis is based on the "good/bad" customer definition of the previously described practical model to ensure to analyze the correlation between the defined definitions and the macroeconomic indicators. Moreover, the analysis will be based on a country-/regional level which enables to analyze whether there will be differences between the countries and regions. This chapter describes the statistical methodology used, the data basis followed by the description and interpretation of the results.

5.1. Data Collection and Preparation

For the statistical analysis, two main data sources are required – one representing the customer classification and the second one representing the macroeconomic indicators. For the customer classification, the results from the machine learning model are used. This output is a binary response variable with 0 (=good payment behavior) and 1 (=bad payment behavior). The model provides the output for roughly 630,000 customer transactions between July 2015 and June 2016 for 114 countries within the region EMEA. As the analysis is based on a country-/regional level and shows the change in customer behavior over time, an average of the payment behavior classification is calculated for each country and for each month which leads to a result between the range of 0 and 1. On top of that, some countries only had very limited transactions from just one or a few customers. As one customer cannot represent the average payment behavior of a whole country, the countries with an unrepresentative number of customers were removed. This led to a total of 68 countries in scope of the analysis (cf. Appendix J).

The second data source used for the analysis is the macroeconomic data. Collecting this information was one of the major challenges within the analysis. The aim was to choose the indicators identified as most important within the survey. However, a second requirement was the periodicity and the country itemization. Due to the short time range of the model, data availability on a monthly level was of high importance to get accurate results. On top, ensuring data comparability, the requirement was to choose one data source. The data source providing most indicators taking in mind the periodicity, the country-level and the results from the survey was Bloomberg. Bloomberg is a service providing a wide range of business and market news and data worldwide. A subscription and a special Bloomberg Terminal is necessary to extract the data (Bloomberg, n.d.). The indicators identified for the analysis were the Consumer Price Index taken as an indicator for inflation, the oil price, the unemployment rate and the central bank effective rate as an indicator for interest rate. GDP growth rate would have been a more suitable figure than unemployment rate for the Direction of the Economy category. However, the GDP data is only available on a quarterly basis which would lead to unrepresentative results. A short description of each indicator is provided in the following.

Consumer Price Index

The Consumer Price Index is an indicator providing information on inflation. Inflation has in general two theories on the cause. The cost-push theory outlines that higher wages and raw material costs lead to an increase in prices. The demand-pull theory explains higher prices since the demand is higher than the supply which is supported by tax cuts, higher government spending or a wage increase. A price indicator measures the changes in particular prices or groups of prices. It measures the change in price level of a certain basket of goods. The indicator used in the analysis is measured in percentage change to the previous month (Stutely, 1992, pp. 180-186) (Investopedia, n.d.). The indicator taken from Bloomberg is defined as “a measure of prices paid by consumers for a market basket of consumer goods and services. The yearly (or monthly) growth rates represent the inflation rate.” (Bloomberg, 2015-2016). The consumer price index is available for 55 countries making it the indicator with the highest availability.

(Change in) Unemployment Rate

The unemployment rate is self-explanatory. It is defined as the unemployment as a percentage of the total labor force which is the sum of the employed and unemployed population. In general, the unemployment rate is a good indicator to identify the current state within the business cycle. In recessions, there is often a higher unemployment compared to other phases. There are in general two drawbacks of the indicator. First of all, the unemployment rate usually occurs with a time lag and secondly, the notion in countries is different. Germany for example excludes the self-employed from the total work force. However, there are international organizations producing standardized unemployment rates providing a consistent figure (Stutely, 1992, pp. 56-66) (Bloomberg, 2015-2016). The unemployment rate is available for 35 countries.

Central Bank Effective Rate

An interest rate can be defined as the price one must pay for money. The interest rate used in the analysis is the central bank rate. It is the rate at which domestic banks can rent money from the nation's central banks affecting the general lending interest rate and the economic activities within one country. Bloomberg has a very general definition stating "the corresponding country's official central bank rate, as of the corresponding date." (Bloomberg, 2015-2016). Low bank rates support an economic expansion due to low borrowing costs while high bank rates stop economic growth and is used when inflation is too high (Investopedia, n.d.).

Oil Price

The fourth indicator is the oil price. It is the price of crude petroleum and is sensitive to supply and demand. Oil is the major energy source affecting almost every economy. The indicator is traded on the world market. Therefore, the issue with country-related data does not take into consideration. A change in oil price has significant effects on an economy as can be seen in the Table 3. An increase in oil price by $3/barrel leads to a decreasing real GDP, a decrease in unemployment and a decrease in the current account in the major industrial countries as a group. The oil price could be used for each country, leading to a total of 68 in the analysis.

Table 3 Effect of oil price increase (Stutely, 1992, p. 190)

Table 13.3 **Effect of a $3/barrel rise in oil prices**[a]
% change in one year

	USA	Japan	Europe	OECD
Real GDP	−0.1	−0.3	−0.2	−0.2
GDP deflator	0.1	0.3	0.5	0.4
Employment	–	−0.1	−0.1	−0.1
Current account ($bn)	−5	−5	−5	−12

[a] Based on oil at $20 a barrel.

Source: OECD

The two described data sources define the variables x and y used for the analysis. The explanatory variable x is represented by the average macroeconomic indicator per month while the response variable y is the average customer classification class representing the payment behavior of the customer (cf. Figure 13).

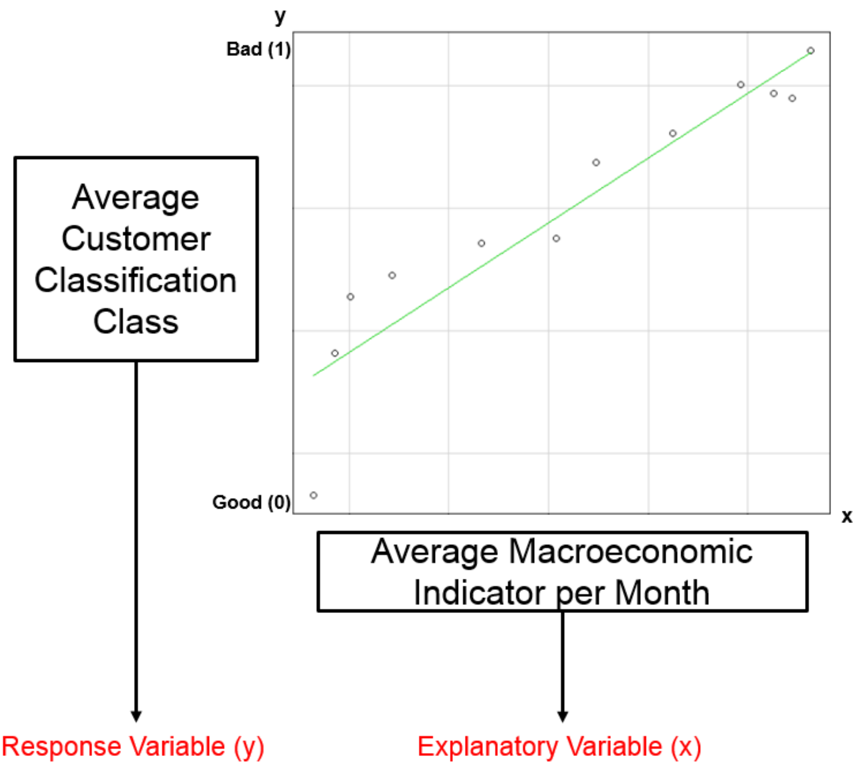


Figure 13 Statistical Variable Definition (created by author)

5.2. Statistical Methodology

The statistical analysis is based on a 3-step-approach. The author conducts a linear regression analysis from which the three steps were derived. The first step is a correlation analysis between the macroeconomic indicators and the classification of the customer. This analysis is constructed on a country- and regional level. A graphical representation with scatterplots helps to identify the relationship and the direction of the relationship. The second step is the significance test of the correlation. Finally, the statistical analysis closes with the formulation of the linear regression line including the coefficients. Based on the complexity of macroeconomic indicators, relationships and the high amount of countries in scope of the analysis, the interpretation of the results is kept on a broad overall level. A more detailed interpretation is represented by four case studies with focus on one country each. For the calculations, the statistical software environment R is used. It is a program for statistical computing and graphics (The R Foundation, n.d.).

The correlation coefficient is calculated using the Pearson Correlation. This is one of the most widely used methods for calculating the correlation coefficient and is named after Karl Pearson (1857-1936) who is often related to as the founder of the modern quantitative analysis. It measures the extend of linear relationship among two variables. It is calculated in the following way:

$$r_p = \frac{\frac{1}{n} * \sum_{i=1}^{n}(x_i - \bar{x}) * (y_i - \bar{y})}{\sqrt{\frac{1}{n} * \sum_{i=1}^{n}(x_i - \bar{x})^2} * \sqrt{\frac{1}{n} * \sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

Equation 3 Pearson Correlation (Eckey, Kosfeld, & Türck, 2008, p. 178)

The Pearson correlation is defined as the division of the covariance by the product of standard deviation of each characteristics x and y. The total number of observations is measured by n while the variables' arithmetic mean is given by $\bar{x}$ and $\bar{y}$. The Pearson correlation measures the linear relationship between the two variables. The result is a value between -1 and 1 because it is set in relation to the standard deviations of the variables (Field, Miles, & Zoe, 2012, pp. 208-210).

The Pearson Correlation provides two main information on the relationship between the independent variable and the dependent variable. Firstly, it provides insights on the direction of the relationship, whether it is a negative or a positive correlation. Secondly, it reflects the strength of the relationship varying from -1 which ensembles a perfect negative correlation to 1 representing a perfect positive correlation (Diekhoff, 1992, p. 219).

The correlation coefficient is influenced by the number of observations. If the correlation is based on only a few number of observations, the correlation needs to be closer to -1 or 1 to be statistically significant. Therefore, it is necessary to test as a second step the statistical significance of the correlation. There are two factors considered when testing the significance: R^2 and the p-value. R^2 is a percentage value that explains how well the response variable variation is explained by the linear regression line. The higher the value, the better the data fits to the regression line. The peculiarity of the simple linear regression is that R^2 is equal to the squared Pearson correlation coefficient. The other methodology used is a hypothesis test to test the significance of the correlation coefficient. A standard method used is the p-value which is a value between 0 and 1 representing the probability that the observations have occurred if the null hypothesis were true. The two hypotheses are:

(1) Null Hypothesis: H_0: $r = 0$

(2) Alternate Hypothesis: H_a: $r \neq 0$

A correlation coefficient equal to zero represents an insignificant relationship. However, the higher the Pearson correlation coefficient, the more the data cloud is plotted around the regression line. As a significance level $\alpha=0.05$ is chosen. The null hypothesis will be rejected in case the p-value is less than 0.05. If the null hypothesis is rejected, it means that there is enough evidence that the relationship is significant (Holmes, Illowsky, & Dean, 2017, pp. 563-564).

The third step in the statistical analysis methodology is the formulation of the linear regression line. The linear regression makes it possible for a given macroeconomic indicator to identify the classification representing the payment behavior of the customer. The linear regression line is represented by the simple equation:

$$y = a + bx$$

Equation 4 Linear equation (Holmes, Illowsky, & Dean, 2017, p. 564)

The variable y represents the independent variable while x represents the dependent variable. The result is a straight regression line. The value b is called the regression coefficient of y on x. It is set equal to the slope. The detailed methodology of the linear regression was described in the previous chapter (cf. Chapter 3.1.) being the reason for why the OLS methodology will not be outlined in detail once again.

5.3. Results of Statistical Analysis

The correlation analysis and significance test were performed with the four macroeconomic indicators oil price, interest rate, unemployment rate and CPI because of the afore-mentioned reasons. The author decided not to describe in detail the results of the analysis due to complexity (194 country- and 69 regional correlations). The results are shown in detail in appendix K. The following presents a summary of the results while being interpreted in the next sub-chapter.

The correlation between the oil price and the predicted customer classification is statistically significant in 34 of the 68 countries (in 50% of the cases) with 18 positive and 16 negative correlated relationships. Having a look at the regions, there are in total 9 out of 20 (45%) regions showing a statistically significant correlation with 4 positively and 5 negatively correlated countries.

The analysis of the interest rate and the average customer classification shows relatively speaking most of the significant correlations among all chosen indicators. 22 of the total analyzed 36 countries proof significant correlations counting for 61%. 91% of the correlations have a positive direction, meaning that the payment behavior worsens (increase from 0 to 1) once the interest rate increases. Considering the analysis on a regional level, 10 out of 15 regions (67%) show statistically significant correlations between the interest rate and the average customer classification. Only one of the correlations is negatively correlated, namely the region Southern Africa.

The third macroeconomic indicator analyzed was the unemployment rate. The unemployment rate correlated significantly in 19 out of 35 countries (54%) with 68% positive directions. Within the regional analysis, the positive relationship became even clearer. 50% of the total 14 regions proved significant correlations with only one negative.

Finally, the fourth analysis investigated the correlation between the consumer price index being an indicator for inflation and the payment behavior of customers. This led to significant correlations in 27 out of 55 countries (49%) and 11 out of 20 regions (55%). In this example, the direction of correlation does not seem to be as clear as in the previous examples. 62% of the countries and only 54% of the regions showed a positively related direction of the correlations.

5.4. Interpretation of Results

The results in general prove significant correlations in some regions, however not in all. Getting deeper into the analysis, all four indicators are analyzed within the next paragraphs.

Starting with the indicator oil price, having a look at the regions and countries showing a significant correlation, it can be summarized that especially countries with a higher oil dependency show correlated relationships (cf. Appendix L). Most countries demonstrate negative correlations. This means that a decrease in oil price leads to an increase in classification class, meaning an increase from 0 to 1, basically a deterioration of payment behavior. A country-specific example will be provided in more detail below as a case-study. Nevertheless, there exist some cases contradicting this observation. Russia for example, a country with an oil rent of 5.5% of GDP in 2015 does not show a significant correlation at all. On top of that, there are countries having a significantly positive correlation but not being directly dependent on oil as a producer such as France, Malta, Hungary or Slovenia. It would mean that in France the customer payment behavior gets better as soon as the oil price increases. However, the French economy's GDP is not dependent on the oil price directly. A counter-example is Saudi Arabia. Saudi Arabia is the country with the highest oil dependency, showing a decreasing trend but still an oil rent of 22.5% of GDP in 2016 (42.9% in 2014) (The World Bank, n.d.). The analysis of Saudi Arabia, however, shows a significant positive correlation of 0.79. This would mean that the payment behavior worsens with an increasing oil price which contradicts the previous country analysis of Saudi Arabia (cf. chapter 3.2.2.). It was stated that the country faced economic difficulties in 2015/2016 due to a decreasing oil price. Nevertheless, it is possible to assume that countries with a low oil rent of GDP have a positive correlation (for example France, Denmark, Finland, Switzerland, UK) while countries with a high oil rent of GDP show a negative correlation (for example Kazakhstan, Bahrain, Egypt, Kuwait, Oman, UAE, Algeria, Nigeria). This can be explained as the last-mentioned countries are producers of oil being dependent on a high oil price while the other countries use oil and further process it and therefore favor low oil prices.

As already mentioned before, the analysis of the interest rate mainly shows positive correlations which implies that an increase in interest rate leads to an increase from 0 to 1 meaning to a worsening payment behavior. The analysis of the interest rate is even the analysis with the strongest correlations. Especially European countries show strong correlations of around 0.9. Yet, there are three countries with a negative correlation, namely Cyprus, Latvia and Southern Africa. As Cyprus and Latvia are both countries within the EURO area, it would have been expected to show a similar positive correlation as all other countries. Southern Africa had an increase in interest rate from 5.89% in July 2015 to 6.97% in June 2016. Nevertheless, the payment behavior increased slightly. This contradicts the logic of the other countries. The interest rate increase is even quite significant. Apart from that, 15 countries do not show a correlated behavior between payment behavior and interest rate change within the country. Which shows again, that there are correlations within some countries however no causal relationship (cf. Appendix K).

The correlation analysis with the macroeconomic indicator unemployment rate shows mostly positive correlations. This can be interpreted as an increase in unemployment rate leads to an increase in customer classification from 0 to 1 meaning to a worse payment behavior. As already analyzed within the country comparison, in many countries the consumer spending and the overall economic development are dependent on the unemployment rate. Once it worsens, it leads to mistrust and uncertainty, slowing down a country's economic growth. Nevertheless, this is not a statement which can be generalized for the results of the correlation analysis. There are again three types of results. In total, 13 countries showed the just mentioned significant positive correlation. However, 6 countries displayed a negative correlation namely Cyprus, Austria, Estonia, Iceland, Norway and Switzerland. These countries either have an increasing or a decreasing trend with regards to the unemployment rate with a contradicting development in customer payment behavior. A reason for this can be that other economic developments within the country are more significant working against the trend of the unemployment rate as already outlined in the description of the country snapshots. The third result which can be recognized is the non-correlated relationship. One reason for this could be that the change in unemployment is so insignificant (8% in Belgium in July 2015 to 8.2% in June 2016), that it might not have a significant impact for a developed country such as Belgium and therefore leads to the uncorrelated result. The period of observation is too short to show significant changes in both, change in indicator and change in payment behavior.

The CPI analysis shows as all other indicators a diverse picture. In general, there is a trend observable to positive-directed correlations. This can be interpreted as an increase in CPI leads to a worse payment behavior. However, the trend is not as clear as in other observations. As already mentioned above, 17 countries showed a positive while 10 showed a negative trend. Moreover, around half of all countries do not show a correlation at all.

Comparing the regional results with the results for the countries belonging to each region there is another phenomenon observable called the Simpson's paradox. For example, considering the correlations for the region Nordics & Baltics for the indicator interest rate, the region in general implies a strong positive correlation of 0.9 with a p-value of 0.000065. The consideration of the regions, however, leads to false conclusion. As the country Sweden belongs to this region, one might conclude that this country also has a positive correlation. However, the county analysis shows, that Sweden, Lithuania and Iceland do not have significant correlations at all although the overall region analysis proves it. The Simpson's paradox is named after Edward H. Simpson who first introduced the phenomenon. It outlines the effect that a trend can occur in different data sets but can disappear when the data is aggregated (Blyth, 1972). This is the reason why the author conducted all calculations not only on the regional- but also on the country-level to avoid false conclusions.

For each of the significantly correlated regions, a linear regression analysis was performed (cf. Appendix K). The linear regression function provides insides into how much the customer classification class will change in case the macroeconomic indicator changes by one unit. In general, the slopes and therefore the change in customer classification are very small. Typically, it is less than 0.1 for all indicators. There are a few exceptions for the three indicators CPI, interest rate and unemployment rate. The linear regression analysis for the indicator CPI showed the highest change in customer classification due to a change in inflation for the country Malta with a slope of 0.15. Kazakhstan is the huge exception in the linear regression analysis for the indicator unemployment rate with a slope of 0.49 followed by Malta with a slope of 0.19. For Kazakhstan this would mean that a change in unemployment rate by 1% would lead to a change in customer class rate by 0.5 which is very significant and might even be a hint for a false correlation. The linear regression with the indicator interest rate shows the highest variations among the slopes. Countries such as Greece, Luxembourg, Malta, Slovakia and Slovenia have values higher than 0.1. A detailed analysis of Greece will be provided below as a case study example.

Summarizing the results presented, it can be clearly stated that there are significant correlations when analyzing the different indicators in relation with the customer payment behavior. However, it cannot be generally said that the correlation is also causal as there are many countries not showing a significant result. A causal relationship can be interpreted as a cause-effect relationship. Transferring this to the analysis, it would mean that macroeconomic indicators would be the cause for the change in customer classification which is the effect. In some countries, it might be the case. However, it would have been necessary to analyze each country's situation to find out whether there are other affects influencing the relationship. An example would be as mentioned before that other economic changes outweigh the effect of the analyzed indicator. On top of that, the linear regression analysis shows that for most of the countries, a change in indicator does lead to a change in customer payment behavior. However, the impact is very small. Nevertheless, it needs to keep in mind that the analysis only focuses on values between 0 and 1 which provides a different range when talking about a change of 0.01.

Due to the complexity of countries within the analysis a detailed view on each country is not possible. The following presents in detail four case studies, one for each indicator.

Analysis: Oil Price ~ Customer Classification in UAE

Chapter 3.2.2. already outlined the importance of United Arab Emirates for the region Middle East & Egypt. Having a look at the oil rents as a percentage of GDP, the share in 2014 was 24% with a decreasing trend to 11.2% in 2016 (The World Bank, n.d.). This decrease is due to the governmental ambition of diversifying the industry due to the economy's high dependency on the effects of the oil price. Having a look at the correlation analysis between the oil price and the customer payment behavior, one gets a result of -0.76.

The scatterplot in Figure 14 additionally portraits the negative direction of the analysis. A decreasing trend can be analyzed. Once the oil price increases, the payment behavior gets better. The analysis also proves the correlation to be statistically significant with a p-value of less than the significance level α = 0.05. Having a look on the linear regression analysis, it leads to the following function:

$$Customer\ Classification = 0.639171 - 0{,}0012098 * Oil\ Price$$

Equation 5 Regression function Oil Price UAE (created by author)

Looking at the function, it says by every change in oil price, the class changes by 0.00121. In general, the change seems to be very small. However, it is necessary to keep in mind, that it can only take a value between 0 and 1, while 0 represents a good customer and 1 represents a bad customer. Further, the oil price is just one of various indicators which might lead to an alteration of the payment behavior.

The analysis leads to the conclusion and interpretation that the payment behavior of a country with a high dependency on oil production can be influenced by oil price changes. This goes hand in hand with the results of the surveys. The oil price was stated as an important factor to consider within a customer credit risk assessment.

UAE : Indicator Oil Price

```
> cor(UAEOil$Oil_Price,UAEOil$Class)
[1] -0.7613209

> UAEOilregression<-lm(Class~Oil_Price,data=UAEOil)
> summary(UAEOilregression)

Call:
lm(formula = Class ~ Oil_Price, data = UAEOil)

Residuals:
       Min         1Q     Median         3Q        Max
-0.0096473 -0.0054573 -0.0004844  0.0050663  0.0099230

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.6391717  0.0181402  35.235 8.04e-12 ***
Oil_Price   -0.0012098  0.0003258  -3.713  0.00402 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.007323 on 10 degrees of freedom
Multiple R-squared:  0.5796,    Adjusted R-squared:  0.5376
F-statistic: 13.79 on 1 and 10 DF,  p-value: 0.00402
```

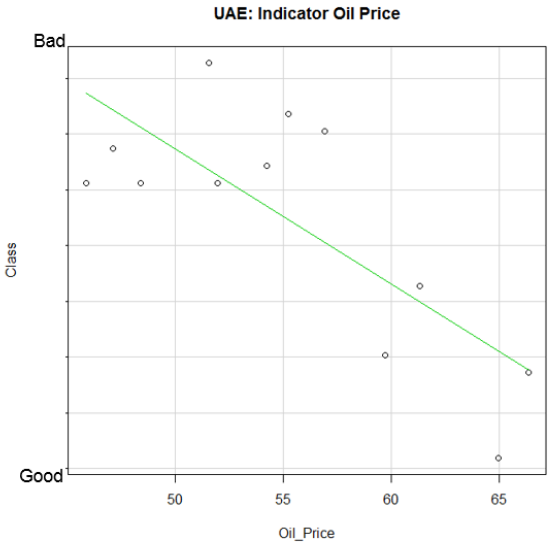


Figure 14 Statistical Analysis of Macroeconomic Indicator Oil Price in UAE (created by author)

Analysis: Interest Rate ~ Customer Classification in Germany compared to Greece

The second case study elaborates the correlation of the payment behavior with the interest rate in Germany and contrasts it with an example in Greece. The interest rate, an indicator seen as important by the credit manager survey, shows the highest correlation in Germany among the analyzed countries.

Having a look at the scatterplot in Figure 15, a clear linear relationship is observable. Additionally, a positive direction of the relationship can be interpreted as customers in Germany experiencing a deterioration in payment behavior once the interest rate increases. The reason for this can be as lending and investment becomes more expensive as the interest rate increases leading to a worse payment behavior.

The regression formula from the linear regression analysis is the following:

$$Customer\ Classification = 0.055093 + 0.044231 * Interest\ Rate$$

Equation 6 Regression Function Interest Rate in Germany (created by author)

An increase in the interest rate by one unit leads to an increase in customer payment classification of 0.044. Again, the change in customer payment behavior seems to be very small. However, Germany is a country with a good payment behavior compared to other European countries. On top of that, the interest rate level in the European Union is negative within the period 2015-2016 providing a general favorable environment for lending. This can be reasons for the very small changes in payment behavior. Nevertheless, there is a significant and very highly correlated relationship between the interest rate and the payment behavior in Germany.

Germany: Indicator Interest Rate

```
> cor(DEIR$IR,DEIR$Class)
[1] 0.9277406

> summary(DEIRregression)

Call:
lm(formula = Class ~ IR, data = DEIR)

Residuals:
       Min         1Q     Median         3Q        Max 
-0.0032298 -0.0012275  0.0001374  0.0017701  0.0024649 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 0.055093   0.001430  38.529 3.31e-12 ***
IR          0.044231   0.005627   7.861 1.37e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '

Residual standard error: 0.002106 on 10 degrees of freedom
Multiple R-squared:  0.8607,	Adjusted R-squared:  0.8468 
F-statistic: 61.79 on 1 and 10 DF,  p-value: 0.00001373
```

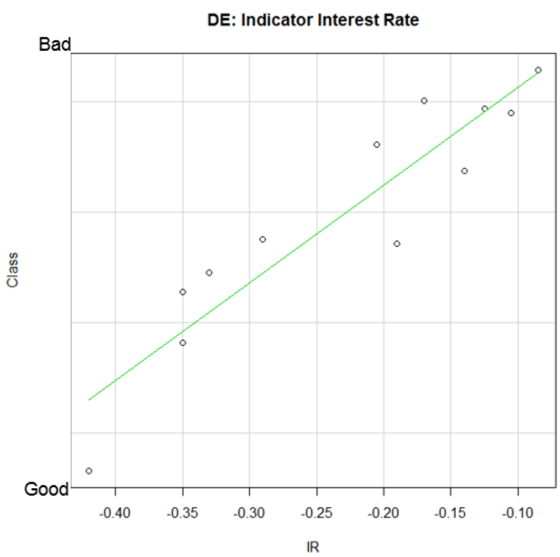


Figure 15 Statistical Analysis of Macroeconomic Indicator Interest Rate in Germany (created by author)

Considering the analysis of Greece compared to Germany, the main change as already briefly mentioned before are the slopes of the regression functions. The linear function for the relation between the payment behavior class and the interest rate is the following:

$$Customer\ Classification = 0.4709 + 0.2950 * Interest\ Rate$$

Equation 7 Regression Function Interest Rate in Greece

Considering both functions, Greece shows a higher sensitivity to changes in interest rate compared to Germany. A possible reason for this observation is the financial situation and the strength of economies as outlined within the comparison of the regions (cf. sub-chapter 3.2.2.). This supports the conclusion that there is a different credit risk in every country leading to different payment behaviors and sensitivities to changes in certain indicators as well as the overall industry (cf. Figure 16).

```
> cor(GRIR$IR,GRIR$Class)
[1] 0.8594249

> summary(GRIRregression)

Call:
lm(formula = Class ~ IR, data = GRIR)

Residuals:
      Min        1Q    Median        3Q       Max
-0.0259145 -0.0163997  0.0002184  0.0127741  0.0295864

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   0.4709     0.0141  33.384 1.37e-11 ***
IR            0.2950     0.0555   5.316  0.00034 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.02077 on 10 degrees of freedom
Multiple R-squared:  0.7386,    Adjusted R-squared:  0.7125
F-statistic: 28.26 on 1 and 10 DF,  p-value: 0.0003398
```

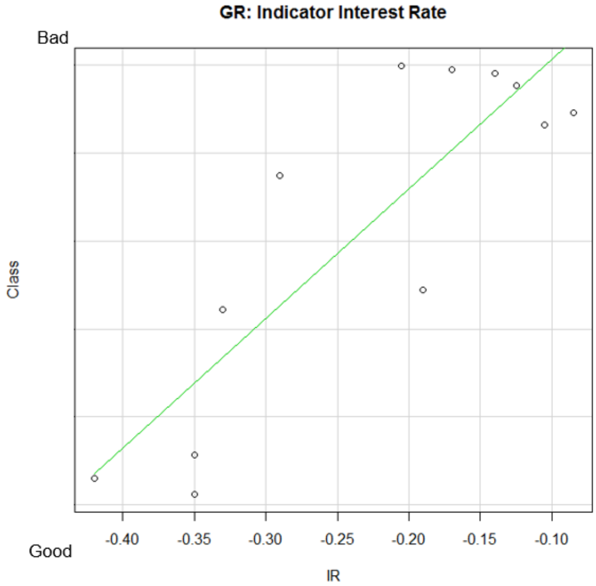


Figure 16 Statistical Analysis of Macroeconomic Indicator Interest Rate in Greece (created by author)

<u>Analysis: Unemployment Rate ~ Customer Classification in Austria</u>

The country Austria is chosen for the case study on the macroeconomic indicator unemployment rate because the results contradict the logical argumentation. As already outlined before, most of the significant correlations proved a positive direction leading to a better payment behavior once the unemployment rate decreased. This logic also fits to the economic development described in sub-chapter 3.2.2. A lower unemployment rate is a driver for a higher consumer spending boosting economic growth. However, the analysis on Austria shows a significant negative correlation of -0.83 (cf. Figure 17).

This negative direction implies an improvement in payment behavior once the unemployment rate increases. The regression formulation would mean that a decrease in unemployment rate would decrease the payment classification class by 0.022793. There are several reasons for these results. It can be that a spurious correlation is observable here. Another explanation could be that there are other economic effects working against the unemployment rate and balancing the effects. Factors leading to this will be outlined as a summary after the case studies.

```
> cor(ATUR$UR,ATUR$Class)
[1] -0.8328897

> summary(ATURregression)

Call:
lm(formula = Class ~ UR, data = ATUR)

Residuals:
       Min         1Q     Median         3Q        Max
-0.0068430 -0.0015277 -0.0005024  0.0025917  0.0044699

Coefficients:
             Estimate Std. Error t value  Pr(>|t|)
(Intercept)  0.176507   0.028354   6.225 0.0000982 ***
UR          -0.022793   0.004789  -4.759   0.00077 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.003375 on 10 degrees of freedom
Multiple R-squared:  0.6937,    Adjusted R-squared:  0.6631
F-statistic: 22.65 on 1 and 10 DF,  p-value: 0.0007697
```

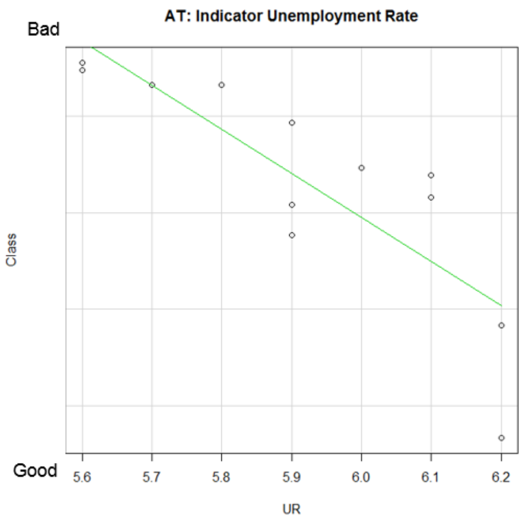


Figure 17 Statistical Analysis of Macroeconomic Indicator Unemployment Rate in Austria (created by author)

<u>Analysis: CPI/Inflation ~ Customer Classification in Ukraine</u>

The last case study taken into consideration is the inflation in Ukraine. Ukraine was chosen as an example for this indicator because the country has the largest change in CPI within the period. However, the correlation analysis does not show any significant correlation. The correlation coefficient is only -0.44676 with a p-value of 0.144. Additionally, the scatterplot does not show a linear representation (cf. Figure 18).

Although there is a significant change in CPI in Ukraine observable over the analyzed period, it is impossible to observe a significant correlation. On top of that, the payment behavior improved with a higher inflation which also contradicts the logical development of economies.

```
> cor(Ukraine$CPI,Ukraine$Class)
[1] -0.4482108

> CPIUkraineregression<-lm(Class~CPI,data=CPIUkraine)
> summary(CPIUkraineregression)

Call:
lm(formula = Class ~ CPI, data = CPIUkraine)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.027612 -0.011758 -0.000494  0.016004  0.026056 

Coefficients:
              Estimate Std. Error t value       Pr(>|t|)    
(Intercept)  0.2178129  0.0126239  17.254 0.00000000905 ***
CPI         -0.0005158  0.0003253  -1.586          0.144    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 

Residual standard error: 0.01994 on 10 degrees of freedom
Multiple R-squared:  0.2009,	Adjusted R-squared:  0.121 
F-statistic: 2.514 on 1 and 10 DF,  p-value: 0.1439
```

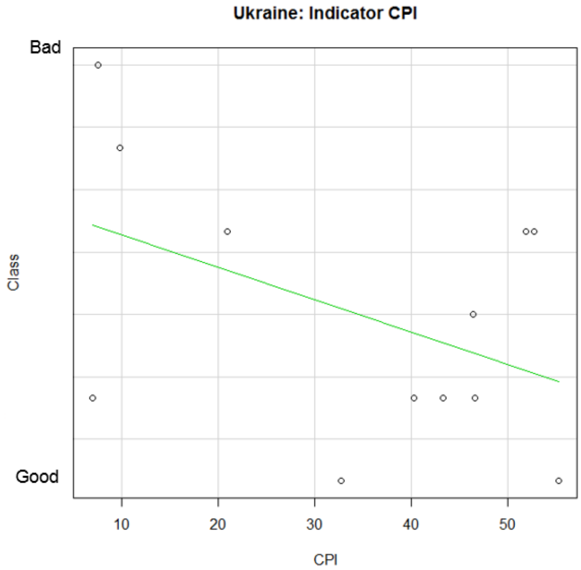


Figure 18 Statistical Analysis of Macroeconomic Indicator CPI in Ukraine (created by author)

The four case studies show completely different results from different regions. The first two cases proved significant and logical correlations which fit to the described economic developments and the results of the survey. However, the other two cases showed results which do not fit to the hypotheses. There are several factors which can be potential reasons for the contradicting results observed in the last two cases:

The statistical model is based on data of a twelve-month period. This short time range can lead to difficulties especially with regards to macroeconomic indicators. A business cycle including the four periods – expansion, peak, recession, trough – can last for several years (Stevens, n.d.) (Wilkinson, 2013). Therefore, a consideration of twelve months is not sufficient to include not only significant changes within one indicator but also the impacts on the economy which leads to the second limitation.

Macroeconomic indicators are subject to time lags meaning a delay between the economic action and the consequence. As the model is only based on twelve months, it can happen that the correlations are not significant because the effect on the payment behavior might appear at another point of time and not within the same month. Therefore, it is necessary to include the time lag within the machine learning model to make sure that consequences within the future can be estimated (Pettinger, 2017).

An additional factor influencing the results of the statistical analysis is the number of customers on which the average for one country is calculated. All countries with a statistically unrepresentative number of customers were removed. However, it is questionable what the exact number of unrepresentative customers is. The countries still have different numbers of customers on which the analysis is based. The small number of customers can lead to unrepresentative results leading to the absence of significant correlations, spurious correlations or an irrational correlation direction.

The results of the statistical analysis depend on the underlying “good/bad” definition and the statistical methodology used. Other figures such as delayed payments or other definition parameters could lead to a different classification. However, the definition is based on past behavior and internal customer data and serves as the basis for the model. Therefore, it was taken as given. Hence, the statistical methodology used can also lead to the different results among the countries. With the Pearson correlation coefficient, the linear correlation was proved. This correlation is very subject to outliers. However, the linear regression is the best linear approximation and comparisons with the Spearman correlation led to similar results. (Angrist & Pischke, 2009). Nevertheless, some countries might have a correlation between the macroeconomic indicator and the classification, but not a linear one leading to a non-significant correlation.

The last worth-mentioning factor is the quality of the macroeconomic indicators. The data was taken from Bloomberg. However, Bloomberg again uses different sources. In countries struggling with corruption or a bad technological and communication infrastructure, a good data quality cannot be taken as granted (Jerven, 2014) (Beguy, 2016).

6. Automated credit decisions as part of Industry 4.0

Credit scoring models especially within the corporate environment gained significance within the last years due to new technologies and stakeholder requirements. Digitalization is the driving force for corporate transformation from manual processing to automation. The automation of credit risk management processes provides new possibilities with regards to the evaluation of the customer's creditworthiness. The following chapter first provides a basic overview of the term Industry 4.0 and presents the so called *7 building blocks* which is a tool for successful transformation. This approach is then applied to credit risk management to identify the impact of Industry 4.0 on the customer credit assessment.

6.1. Definition of Industry 4.0

Industry 4.0 is a term frequently used within the last years. The term describes a new industrial revolution – in the strict sense the fourth industrial revolution. Having a brief look at the past revolutions helps identifying the newness that Industry 4.0 brings along. The first industrial revolution - at the end of the 18th century – was embossed by the introduction of steam and water power which facilitated mechanical production processes. After two centuries, steam and water power was exchanged by electric power enabling mass production with the help of an assembly line. Followed by this, the third industrial revolution, starting at the beginning of the 1970s, was characterized by information technology and the application of electronics. Finally, nowadays the industry faces a fourth industrial revolution which is built on the foundation of connected technologies and processes, analytics, robotics and artificial intelligence (AI) (Schlaepfer & Koch, 2014, p. 3) (EY, 2017, p. 5).

Industry 4.0 can be set equal to a digital transformation. Synonyms often used in literature are 'internet of things (IoT)' or 'industrial internet'. It connects the digital and physical technologies such as advanced materials and manufacturing, analytics, AI and robotics and creates a connection which is called by Deloitte "a physical-to-digital-to-physical connection" (Van Thienen, Clinton, Mahto, & Sniderman, 2016, pp. 1-2). Josef Horák (2016) expressed it similarly: "It's communication, automation, and computer technology. A virtual world will be created as these technologies converge. After that, the virtual world will be reflected in the physical world." (Horák, 2016, p. 575). Summing it up, Industry 4.0 talks about two "worlds", the physical and the virtual or digital world. These two worlds communicate. First, information is captured in the real world which is then delivered and analyzed by the digital world. Machines communicate with each other based on advanced analytics and robotics. Based on the analysis of the information, the machines make decisions and take actions which are transferred back to the physical world (Van Thienen, Clinton, Mahto, & Sniderman, 2016, p. 2).

Figure 19 The four characteristics of Industry 4.0 *(Deloitte, 2016)*

Industry 4.0 has four main characteristics as seen in Figure 19. The first characteristic is the vertical networking of smart production systems. The so called smart factories consist of machines and production plants that communicate with each other. The cyber-physical production systems (CPPSs) build the foundation for the communication between the facilities and support to react quickly to changes or errors. The production is automatically organized and the CPPSs constantly monitor the stock levels, ensure a customer-specific production and enable quick reactions to machinery breakdowns or any other errors that might occur. The focus is primarily on resource management with regards to the use of materials, energy and personnel (Schlaepfer & Koch, 2014, p. 6).

The second characteristic is the horizontal integration via a new generation of global value chain networks. These networks connect the horizontal levels from warehousing, logistics, production to marketing, sales and all kind of services including finance and controlling. The connection of the functions provides real time information along the complete value chain and enables a better coordination resulting in a high degree of transparency and flexibility.

Through-engineering across the entire value chain, being the third characteristic, occurs not only along the entire value chain but also along the full product life cycle. As new products become increasingly important, a new focus on production technologies is set. While developing new products, the production systems create synergies between the production process and the product development. Data along the entire product life cycle needs to be available to create more flexible processes (Schlaepfer & Koch, 2014, p. 7).

The final characteristic of Industry 4.0 is the acceleration through exponential technologies. The success and the driving force of the new industrial revolution is the advanced technology including automated processes, artificial intelligence and robotics. It does not only connect the production processes, it also constantly improves them based on advanced analytics and self-learning mechanisms. This ensures more flexible systems and saves time and costs along the value chain (Schlaepfer & Koch, 2014, p. 8).

Being successful and staying competitive in almost all industries in the 21st century, it is necessary to keep up with the newest industrial revolution and technologies. There exist seven dimensions or so called "building blocks" which provide an overview on what to tackle to complete a successful digital transformation. These seven aspects will be briefly described in the following paragraphs as it builds the foundation for the following subchapter 6.3. Impact of Industry 4.0 on the customer credit risk analysis (Portilla, et al., 2017, pp. 12-14).

1. Data management

One of the most often used terms with regards to data management is Big Data which is in most literature characterized by the three Vs: Volume, Variety and Velocity. Volume describes the huge amount of data available due to the internet access, connected devices and the coinciding constant digitalization of information. Variety stands for the different and various types of data. As data is gathered from many different sources and in different formats, it leads to an unstructured data foundation. The third V is Velocity which outlines the pace of the availability of new data. Data is generated every minute from several sources. Therefore, it is important for business to be able to handle and access real-time data (Iafrate, 2015, pp. 3-11) (Hurwitz, Nugent, & Halper, 2013, p. 57). In some literature, the definition of big data is widened by two more “Vs”. The two terms value and veracity are added. Data is available in a huge amount, however, not every piece of information adds value for a company. It is necessary to identify how much value it creates and how to effectively use a piece of information. Veracity goes along with value. It expresses the correctness of data essential to create added value for a business (Runciman & Gordon, 2014, pp. 4-5).

Keeping in mind the previously described complexity of big data, the significance of data management becomes obvious. Data management covers all activities such as collection, aggregation and processing. Information from all kind of departments and functions (sales, marketing, procurement, finance and other) should all be stored and managed in one system to ensure a connection of processes. Most businesses rely on and heavily invest in cloud-based warehouses providing the advantage of granting access to real time data across all function across the whole globe (Schlaepfer & Koch, 2014, p. 22) (Van Thienen, Clinton, Mahto, & Sniderman, 2016, p. 12) (Portilla, et al., 2017, pp. 12;43-44).

2. Process and workflow automation

The second building block of Industry 4.0 is the process and workflow automation. Many processes within companies are still managed and run manually. The new industrial revolution brings along an ongoing automation of all kind of processes. Fully automated processes depend on robotics which are computer programs taking over manual procedures. It is especially suitable for repetitive and time-consuming tasks and leads to a higher efficiency and cost reduction (Portilla, et al., 2017, p. 45).

3. Advanced analytics and decision automation

Once the data is collected and managed, advanced analytics build the foundation for the automation of processes. Mathematical models analyze and interpret the data and lead to a decision. Advanced analytics contributes to the efficiency as it enables to make more decisions either in a shorter period or even at the same point of time. Moreover, it takes into consideration a larger variety of information and is based on algorithms which, on the one hand, increase the accuracy and, on the other hand, enable to focus on more information than a person could do in a manual process (Schlaepfer & Koch, 2014, p. 12) (Portilla, et al., 2017, pp. 47-48).

4. A cohesive, timely, and flexible infrastructure

As previously defined, big data brings along various challenges: a huge amount of unstructured data at an increasing pace with the risk of irrelevance and incorrectness. Managing and making use of the data properly, an organization needs to have a sophisticated and well-designed infrastructure – an infrastructure such as a cloud or a data lake. They store either structured or unstructured data from all kind of function and processes. It enables to have one source of information available across functions with real-time access (Portilla, et al., 2017, pp. 49-50). The technological integration is an important part when it comes to the implementation of digitalization. Providing information group-wide within a short period of time which is only possible with standardized and professional IT infrastructure. This increases the challenges for organizations. This aspect is further elaborated when analyzing the impact of Industry 4.0 on the credit risk management (Chapter 6.3) (Van Thienen, Clinton, Mahto, & Sniderman, 2016, p. 12) (Dun & Bradstreet, 2009, p. 9) (KPMG, 2017, p. 2).

5. Smart visualization and interfaces

The advanced analytics and algorithms analyze the big data and make decisions. These decisions need to be visible for end users to work with them efficiently. An application such as a dashboard provides a meaningful and useful presentation of the data and information. Transparency is a central issue. Managers need to understand the logic behind the automated decisions to trust the results and to further work with them. This transparency is ensured by a professional dashboard and good visualization (Portilla, et al., 2017, pp. 50-52) (Van Thienen, Clinton, Mahto, & Sniderman, 2016, pp. 11-12).

6. External ecosystem

One of the central issues of the fourth industrial revolution is the connectivity of a corporation with the external ecosystem. It is not only enough to have connected systems within one organization but across businesses and industries. Partnerships with external organizations increase and make use for example of a wider data availability (Portilla, et al., 2017, p. 14).

7. Talent and culture

Having the right technological environment is not sufficient for a success within the Industry 4.0 environment. Creating the culture for change and having an appropriate workforce with the right skills is of high relevance as well. Due to the changing processes, the skills required are different. It is necessary to have sufficient data analysts who can develop the right algorithms and analytics. Apart from that, the scope of work and the therefore required skills of people who used to perform the manual processes changed. They are no longer responsible for reporting but for controlling and analyzing results and using them for further steps (Portilla, et al., 2017, p. 54) (Horák, 2016, p. 580).

The seven building blocks show the complexity of change Industry 4.0 brings along. This creates opportunities when companies are able to keep up with the rapid pace of change and the changes successfully. Further, the seven building blocks show that it is not just a change within one corporate function but within the whole organization, from warehousing and production to sales, marketing and finance. It even enables interfaces across the entire value chain including external partners. Many companies are already successful with regards to smart production connecting supply chain and production facilities with product management and sales. The following chapter focuses on the development of the Corporate Finance function with focus on the Credit Risk Department to access what impact Industry 4.0 has on a credit risk assessment.

6.2. Credit Risk Management 4.0

The Corporate Finance function serves as a business partner within a company. There are several interfaces and cooperation with other functions such as sales, marketing or production. The process of digitalization cannot be successful when focusing only on one function within an entity. It is necessary to connect the different steps to ensure a smooth and efficient workflow. A demonstrative example is the following: The sales function integrates an e-Marketplace to digitalize its selling process. The orders are automatically transferred to the smart production facilities which work hand in hand with the fully automated supply chain. However, this process only runs efficiently and sales can only be granted if the credit decisions are handled quickly. Once an order is placed within the e-Marketplace, the credit approval needs to take place within seconds. If the credit limit approval process would take too much time due to manual process steps it would lead to higher costs and reputational loss (Dun & Bradstreet, 2009, pp. 3-4) (KPMG, 2017, p. 2).

A need for change from manual to automated processes is also necessary because of changing stakeholder’s requirements. No matter who the stakeholder is, whether it is the sales department who requires a quick credit decision, whether it is the shareholder or chief officer who requires actual, higher quality and relevant information or whether it is the customer who requires quick handling and service, all of them ask for real-time, future-related and forward-looking information. These requirements can only be met when applying digital solutions to credit risk processes (EY, 2017, pp. 7-8).

Achieving a successful transformation from manual to automated and digital processes, a company needs to perform several steps. The following paragraphs apply the before mentioned seven building blocks to credit risk management processes on which the assessment of the advantages and limitations in the next sub-chapter is constructed.

1. Data Management

Traditional customer credit assessments heavily relied on internal historical data including historical payment behavior, external ratings from agencies and financial information from the company providing information on liquidity, leverage, cash flow and profitability (Bouteillé & Coogan-Pushner, 2013, p. 79) (Bouteillé & Coogan-Pushner, 2013, pp. 79-90). However, due to the IoT, there is a data potential which goes far beyond the traditional information availability. The agricultural customers provide a good example. This sector and the payment reliability of agricultural customers heavily depend on the weather condition and the quality of the soil. Weather alerts could provide information on future floods or droughts while soil monitors could provide information on ground fertility (Ray, 2017). Using such information increases the knowledge on whether the customer is going to be a reliable payer. However, the availability of such information imposes a new challenge for a credit risk management department. Due to the high availability of unstructured data, there is an urge for efficient data management (Sood & Banka, 2017).

2. Process and Workflow Automation & 3. Advanced Analytics and Decision Automation

Especially credit risk management processes have potential for a transition from manual processes to a digital and automated workflow. Robotics and advanced analytics are the key words within this context. Robotics can be easily used for high-volume but low-value tasks which is typical for many tasks related to credit management. In many corporations, the small customers make up a large percentage of the total client base but only a small part of the total credit limit exposure. Increasing the efficiencies, banks as well as companies use robotics which link different systems, extract the relevant data and complete the workflow automatically. This automation takes place within seconds. (Culp, 2016).

Robotics often goes hand in hand with advanced analytics which is especially useful in financial risk management. Advanced analytics is not a new field in credit risk management. Especially banks already use algorithms for several years trying to automate their processes and enhance their customer scoring predictability. However, due to the new availability of information, new models and algorithms have further advantages. The models do not only determine a credit limit, it also proposes optimal actions and type of protection or insurance and risk scenarios. Moreover, it is possible to use machine learning techniques. The algorithms can be taught to increase the model accuracy over time (Portilla, et al., 2017, p. 47).

4. Cohesive, timely and flexible infrastructure

“Improved data infrastructure is an essential digital capability for the credit risk-management transformation.” (Bahillo, Ganguly, Kremer, & Kristensen, 2016). This citation underlines the importance of an appropriate infrastructure for a digital transformation of credit risk management processes. There are basically two types used by treasury departments and banks: the cloud technology or the data lake. These technologies ensure interfaces with different data banks and systems and provide a ground for the different analytics. A survey conducted by FIS, a global leader in financial services technology, states that around 20% of corporations have already migrated their treasury department to a cloud-based technology and 62% of the corporations are likely to migrate the treasury department to cloud-based systems within the next years because of five main reasons: Security, Scalability, Simplicity, Cost and Maintenance. Cloud providers specialized on data protection due to higher customer requirements. This increases the data security compared to internal technology. Moreover, it is easy to change the capacity of the cloud, it can be used globally over the internet without any additional customer effort and are often cheaper options for corporations as it is based on a subscription-based pricing. They are often easy to use due to standardized interfaces. Maintenance and updates are handled by the providers which minimizes effort and costs for internal IT (FIS, 2017, pp. 1-3;7) (TreasuryToday, 2013) (Rossi, 2015). The cloud technology supports companies to consolidate and aggregate all kind of different data, from customer financial statements over external ratings to unstructured data such as soil quality information from agricultural customers.

5. Smart visualization and interfaces

Especially for the credit risk management function, the visualization of credit limit decisions and customer scoring is key for proper portfolio management. As the decisions derive from advanced analytics, credit managers need to have an interface to work further with the decisions. It needs to go far beyond a monitoring system. The smart interfaces could allow to adjust decisions, apply market scenarios and analyze the portfolio. It offers an overview of the overall credit risk a company faces and provides especially top management and chief financial officers a comprehensive summary without deep and time-consuming analyses (Portilla, et al., 2017, pp. 50-52) (Ballou, Heitger, & Donnell, 2010).

6. External Ecosystem

The external ecosystem was already picked up in the previous topic regarding cloud-technology. An important issue in digitalizing the credit risk function is the cooperation with the external ecosystem. Banks especially cooperate with Fintechs as they provide possibilities to collect bad debt or as they offer digital solutions. Credit risk management within corporations need to partner up with external providers to ensure the high data availability. Such partners can be external rating agencies, debt collection agencies or banks (Portilla, et al., 2017, pp. 52-54) (Balachander & Zacharias, 2017, p. 8).

7. Talent and culture

The digitalization of the credit risk function does not only impact the workflow and processes but also the organizational and personnel set-up. One could assume that credit managers are no longer needed due to the automated credit scoring and credit limit determination processes. This assumption is however not supported by different papers and studies. The scope of work and the daily work of credit managers change involving a change in skills. They mainly focus on controlling and analyzing the results of the automated decisions which require especially analytical skills. However, additional to the “finance” talents, crucial for a successful digital transformation in credit risk departments is the availability of data scientists, statisticians, IT developers and modeling experts. Moreover, a relevant skill of future credit risk management staff is not the availability of technical know-how however the eagerness to learn. The staff should be willing to learn and to be open to innovations and change management which is crucial for digital success (Axson, 2015, p. 5) (Horák, 2016, p. 580) (Portilla, et al., 2017, pp. 54-56).

Concluding, digitalization changes the credit risk management processes from the scratch. It does not only require new technologies and process definitions but also a new organizational set-up, a change in skill-set of existing credit managers and new skills to develop and maintain the scoring algorithm. Despite the advantages of Industry 4.0 for a treasury function, a corporation also needs to keep in mind the limitations. The impact of the new industrial revolution on the customer credit assessment is outlined in the next subchapter.

6.3. Impact of Industry 4.0 on the customer credit risk analysis

> *"A digital transformation of risk would mean a number of changes. Chief among them, risk would capture and manage information from a broader and richer set of data, looking into nontraditional sources like business-review ratings online. I would automate processes it controls and work with others to do the same for decision-heavy processes. […]. Risk would review and reshape its mandate and role to capitalize on its ability to provide faster, more forward-looking, and deeper insights and advice."* (Schlaepfer & Koch, 2014, p. 9)

The citation summarizes the significant changes digitalization brings along in credit risk management. Industry 4.0 and the process of digitalization is unavoidable for companies in order to stay competitive. However, the transformation implicates advantages as well as limitations for the credit risk analysis of customers. Figure 20 summarizes the seven building blogs with the related advantages and limitations being explained in detail below.

	Description	Advantages	Limitations
1 Data Management	IoT: high amount of additional structured and unstructured information on the customer to the traditional data	• Use of new data increases predictability	• Data availability and quality • Data protection → increasing regulatory requirements
2 Process & Workflow Automation	Robotics performs a credit analysis within seconds by linking several processes and systems	• Cost reduction due to workflow automation • Higher level of quality • Process speed and efficiency • Finance staff can focus on other tasks	• Too high dependency on automation, loosing track of risk • High implementation costs
3 Advanced Analytics & Decision Automation	Advanced analytics considers the high amount of data allowing future predictions of payment behavior	• Consideration of more information than a person could • machine learning: no lose of information when a credit analyst leaves	• Maintenance of the algorithm • Regular quality checks
4 Cohesive, timely and flexible infrastructure	Cloud-based technologies or data lakes are key for successful digitalization of credit risk management	• Cloud solution provides many advantages	• Connection of new infrastructure with the existing systems within a company
5 Smart visualization and interfaces	Decision visualizations with the help of dashboards increase transparency and serve for further portfolio analysis.	• Quick overview of the portfolio without extracting information from different systems and manual analyses	• Transparency issues • Standardized visualization might not be suitable for everyone
6 External Ecosystem	Cooperation with external information and service providers increases the data availability	• Connection of different functions within a corporation • Consideration of external knowledge	• Dependence on third parties • No influence on data accuracy • Cost-intensive
7 Talent and culture	The skillset and daily work of a credit analyst change due to the digitalization; additional data specialists are needed.	• Focus on more relevant tasks rather than high-volume but low-value tasks • Add more value to the company	• Motivation problems of credit analysts; fear of being replaced • Not the right skillset to perform the new tasks • Change management

Figure 20 Digitalization of the credit risk management - Advantages and Limitations (created by the author)

6.3.1. Advantages & Limitations

Due to new technologies, interfaces, cooperation and the Internet of Things, more and more data enables new insights and increases the predictability of a customer forecast (Portilla, et al., 2017, p. 43). However, an automated credit limit decision model brings together structured and unstructured data from internal and external sources. The accuracy of the credit limit decisions depends on the data accuracy and availability which is seen as a critical issue. Dun & Bradstreet made the experience that in one hour 200 business telephone numbers, 54 addresses, 92 directorships and 7 company names changed. This shows the fast data movement and changes which leads quickly to an outdated database (Dun & Bradstreet, 2009, p. 10). The available data needs to be of an appropriate quality which is often difficult to achieve in complex organizations. Data sources can be incomplete, inaccurate or contain duplicates leading to the absence or misinterpretation of information and finally wrong credit limit decisions. On top of that, new data regulations and legislations create more burdens on companies as for example the General Data Protection Regulation (GDPR).

Appropriate data standards and policies are enforced by the government increasing complexity and workload for companies (Portilla, et al., 2017, p. 44).

The process and workflow automation guarantees one of the most significant advantages of digitalization for companies – cost savings. Different surveys among risk managers underline the cost saving potential (Portilla, et al., 2017, p. 45) (Bahillo, Ganguly, Kremer, & Kristensen, 2016, p. 5) (Deloitte, 2016, p. 13). There exist three ways to create monetary value for companies. On the one hand, automation protects revenues. Digital processes ensure real-time customer analysis which minimizes the risk of losing sales due to long manual credit risk analysis. On the other hand, digital credit risk management reduces the cost of risk mitigation and the operational costs. As the advanced analytics takes into consideration a higher quantity of data, the credit decisions are more accurate which reduce the costs of loss due to customer default. Operational costs are reduced as resources such as the credit manager can focus on more value-adding tasks rather than manual data management (cf. Figure 21) (Bahillo, Ganguly, Kremer, & Kristensen, 2016, p. 5).

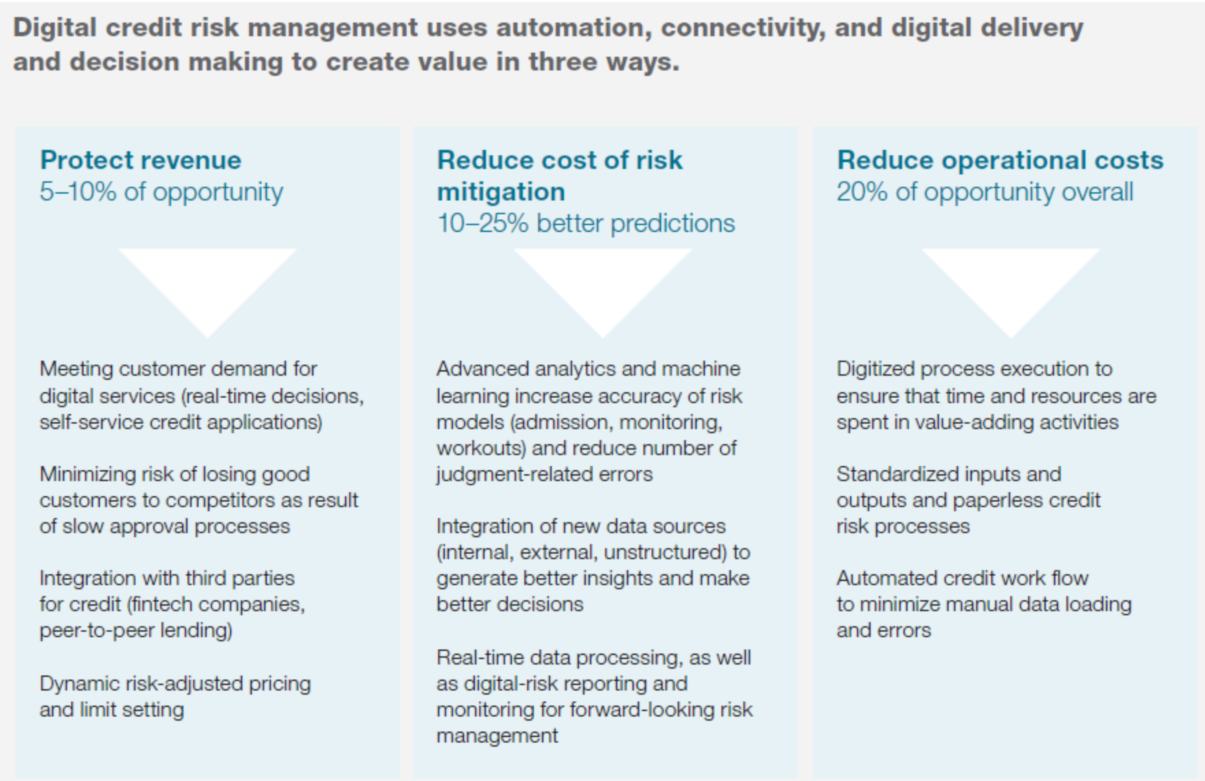


Figure 21 Digital credit risk management uses automation, connectivity, and digital delivery and decision making to create value in three ways (Bahillo J. A., Ganguly, Kremer, & Kristensen, 2016, p. 5)

The process and workflow automation as well as the advanced analytics and decision automation within the credit risk management can significantly improve the level of quality of the credit limit decisions because advanced analytics and machine learning have the ability to consider more information than a person could manually. Furthermore, as machine learning algorithms train themselves by getting more information, there is no loss of knowledge and experience when a credit analyst leaves the department or company. Artificial intelligence „is able to assess significantly more criteria and to flexibly weight them than common rigid decision-making engines. " (Sumper & Merker, 2017, p. 8). AI can even sort out especially difficult cases for manual review. This improves process time and efficiency as well as leads to more decisions at the same time. Yet, process automation and predictive analytics increase the risk of a company's overdependency on automation which can result in loosing track of risk. It is therefore necessary to regularly alter and maintain the algorithm which does not only lead to high costs but also a need for a skilled staff (Portilla, et al., 2017, p. 47).

The technical landscape builds the foundation of the digitalization of processes. In customer credit risk departments, different systems are already in place. Credit managers need to get customer master data, historical payment information or external rating agency reports. All these systems need to be connected once the process is automated. Interfaces are necessary. A cloud-based solution would reduce the complexity of the systems needed as most of the information will be stored in one system. Another advantage is the higher productivity and cost savings and the before mentioned advantages of clouds (Axson, 2015, p. 4). However, the technology is also seen as one of the main barriers for companies to implement digital CRM processes. New IT systems – either a cloud-based solution or a data lake – are required to fit and to interact with the existing IT infrastructure and systems. Data needs to be linked to the existing customer relationship management systems. Especially for large corporations with many systems, probably even different systems in different regions and subsidiaries, this is one of the biggest challenges of Industry 4.0.

The visualization of credit limit decisions through a dashboard solution assists the credit managers to get a quick overview of the portfolio without extracting information from different systems and manual analyses. This saves time and costs and leads to a more efficient workflow. However, a huge issue with regards to dashboards is the urge for transparency. Credit managers' work depends on understanding the reasoning behind the automatically created decisions in order to manage the portfolio successfully for the future. If transparency is not ensured, it can lead to either inefficient or even counterproductive decisions. Moreover, there is one key requirement with regards to dashboards which is the customization. If this requirement is fulfilled, every credit manager can use the tool in the way it suits him/her. However, if customization is not possible, it can lead to inefficient use of the tool because the credit manager cannot adjust the tool in order to see the information he/she wishes or needs (KPMG, 2017, p. 3) (Portilla, et al., 2017, p. 52).

The external ecosystem supports communication between different parties and stakeholders. It connects the different functions within one corporation as well as the cooperation with external information providers. This ensures the consideration of external knowledge. However, it is necessary to value this against the disadvantages. Including external providers always implies a certain dependency lacking influence on data accuracy and availability. Additionally, involving external parties increases costs. Rating agencies, for example, provide companies with country and customer ratings on a regular basis in exchange for a monthly fee. The additional costs need to be valued against the additional information value for customer default predictability (Portilla, et al., 2017, p. 54).

The last aspect to consider with regards to limitations and advantages of digitalization for credit risk management are the talents and culture within the organization. As the daily work of credit managers shifts due to the automated process, they do not longer have to focus on high-volume but low-value tasks but can concentrate on more relevant tasks adding additional value to the corporation. According to a survey conducted by Accenture, by 2020, finance staff spends up to 75% of their time on decision support, performance management and analytics (25% in 2015) (Axson, 2015, p. 5). In contrast, automation of processes can always imply a feeling of replacement of human staff. Effective change management, communicating the right message and vision and creating a culture of innovation is an important feature. Additionally, there is the risk of not having the people with the right skills due to the change in skillset (Axson, 2015, p. 5) (Portilla, et al., 2017, p. 56).

Change management is the relevant keyword in overcoming the challenges. A well-planned implementation and strategy support companies during the shift from one industrialization to the other. Nevertheless, it can be summarized that credit risk management provides processes which are suitable for digitalization. It will be the future in order to stay competitive for corporations and improve the management of credit risk in a fast-changing, globalized business environment.

7. Evaluation

Summarizing the results from the literature review, the surveys and the statistical analysis, a divided picture arises. The literature and the studies clearly prove a relationship between credit risk and macroeconomic indicators emphasizing the importance of considering the economic aspects when assessing a customer. Moreover, the regional analysis showed that some countries are more subject to changes for example in the oil price or exports than others. The following evaluation discusses the main findings as well as the limitations and suggests further steps that arose from this thesis research.

7.1 Evaluation of results

The internal as well as external survey conform with the literature. Experts within the field of credit risk management evaluate the impact and importance of the topic of macroeconomic indicators when assessing the customer’s payment behavior. Based on the results of the literature review and the survey, it is even possible to create a list with the indicators taken into consideration when assessing a customer which is summarized in Table 4.

However, when having a look at the statistical analysis, the results are not as clear as provided by the survey. There are significant correlations in some countries, yet, the analysis does not prove a causal relationship. This does either mean that there exist only causal relationships within some countries in EMEA or that there exist no causal relationships and the observed correlations are only spurious.

Table 4 Overview of macroeconomic indicators in credit scoring (created by author)

Indicator Category	Literature Review	Country Analysis	Internal Survey	External Survey
The Direction of the Economy	• *Real GDP growth* • Growth of industrial production • Change in unemployment	• *Real GDP growth* • Change in unemployment	• *Real GDP growth* • Change in unemployment/Industrial production	• *Real GDP growth*
Financial Market Conditions	• *Interest Rates* • Stock market returns • Stock market volatility • Stock market indices • *Exchange rates*	• *Interest rates* • *Exchange rates*	• *Interest Rate* • *Exchange Rate*	• *Interest Rate* • *Exchange Rate*
General Market Conditions	• Unemployment • *Inflation* • Capacity utilization • *GDP* • Industrial Production • *Consumption Indicators* • *Export & Import Indicators* • Corporate Insolvency Rate • Corporate Credit Share	• *Inflation* • *GDP* • *Consumption indicators* • *Export indicators* • Wage rate	• *Inflation (CPI)* • *GDP* • *Consumption indicators* • *Export & Import indicators*	• Unemployment • *Inflation* • *GDP* • Industrial Production • *Consumption* • *Export & Import* • Corporate Insolvency Rate
Country & Industry specific indicators		• *Oil price* • Raw material prices • Industry-related indicators (automotive industry for CZ) • Political decisions	• *Oil price* • Commodity prices • Political situation	• *Oil/Gas price* • Commodity prices • Political situation
Indicators for statistical analysis	Direction of the Economy: Change in unemployment* Financial Market Conditions: Interest Rate General Market Conditions: CPI Country & Industry specific indicators: Oil price			

* GDP growth only quarterly available, therefore not suitable for statistical analysis

Especially due to the different views on the impact of macroeconomic indicators on customer payment behavior, it is necessary to keep in mind the limitations already mentioned earlier. The absence of significant correlations as well as the different results can be due to the data availability and quality. Some countries' statistical offices provide better information than others. On top of that, although GDP being identified as the most important indicator within the survey, it was not possible to test it in the statistical analysis due to the short time range of the model. It was necessary to choose indicators which might not have such a big impact on every country. Apart from the short time range of the model, some countries' results were based on a very small customer sample. Additionally, the time lag often discussed within economics was also excluded during the analysis. A more detailed analysis of every countries' economy and political situation might provide reasons for why significant correlations with some indicators can be seen only in certain countries. However, due to the high amount of countries taken into consideration, this detailed analysis was not in scope of the thesis. Keeping the limitations in mind and the trends seen within the statistical analysis (e.g. higher oil price dependency in countries with high oil rents as a % of GDP), it is possible to assume that macroeconomic indicators can have an impact on the customer's payment behavior. The consideration of these additional factors within a credit risk analysis can lead to a higher model predictability. This however needs to be tested in more detail which will be outlined within the next chapter 7.2. Further Steps.

Nevertheless, one can see that there exist differences between the analyzed countries with regards to the payment behavior, DSO and the credit risk. This can serve as an explanation for why some countries are more vulnerable to macroeconomic changes than others explaining the non-existence of the causal effect among all countries.

Evaluating the analysis of the impact of digitalization on the customer credit risk assessment, it clearly outlines the urge for changing from manual to automatic processes to ensure a smooth ongoing along the entire value chain. The advancing technology within the last years supports the change and provides an environment making is much easier for companies to include information which goes far beyond the traditional data used in a credit risk assessment so far. The smart visualization of the results and the predictive analytics used to compile the information and score the customer shift the daily work of a credit manager from administrative to more future-related tasks. The limitations outlined previously such as the data availability and quality, the high dependency on information technology or the motivation problems of credit managers due to the fear of being replaced are all issues that need a high degree of consideration. Especially the data basis is crucial for the success of the credit risk management. The predictive model can make decisions. However, the decisions are based on the underlying data source. Inaccurate information leads to a wrong management of the credit portfolio having significant impact on the company's working capital management.

7.2 Further Steps

Due to the different results from the survey and the statistical analysis, there are three main steps proposed for further research.

Firstly, the survey was only conducted with experts from the field of credit risk management. However, the second important part to consider is macroeconomics. An additional survey with experts from the just mentioned field might lead to additional and potentially more relevant indicators. As an example, the political indicators such as political confidence or other early warning indicators such as consumer confidence are ignored within the thesis as these indicators were not suggested within the literature as well as within the survey. However, it might eliminate limitations in the statistical model such as the time lag. The external survey identified the training potential of the credit managers within the field of macroeconomics. Expert advice from the field might lead to a better choice of indicators.

Secondly, it is necessary to identify whether macroeconomic indicators improve the predictive model. A further step would be to include the indictors within the model, run the model again and access the type I and type II error rates with the help of the confusion matrix. In case both error rates decreased especially in countries being dependent on macroeconomic indicators such as the oil price, it would show that the model predictability can be improved including the indicators.

The last next step would be to improve the statistical testing methodology. Firth of all, the time range of the model will be extended on a regular basis within the next months. The time range underlying the thesis was very short due to the machine learning approach. Additional years will be added one after the other to train the model. Once the model includes several years, the statistical analysis can be conducted again. Then even quarterly GDP data could be used. This might lead to completely different results as changes within macroeconomics often appear over several and not within one year. On top of that, a different regression model can be used additionally to test for other than linear relationships.

8. Conclusion

The thesis discusses the change in customer's credit risk assessment processes due to digitalization and aimed at identifying the impact of macroeconomic indicators on a credit risk assessment and whether the indicators should be considered within an automated credit scoring model.

Corporations have experienced the impact of credit risk especially during the financial crisis in 2008 and have started to implement solid credit risk management processes. Within the scope of the fourth industrialization and the digitalization, new possibilities arise to automate credit scoring models with the help of predictive analytics. This change has the advantages of considering a larger amount of customer data beyond the traditional information used by a personal judgement and of shifting the scope of the credit risk managers from collecting and maintaining information to a more future-oriented working behavior. Nevertheless, a change always implies certain drawbacks. An automated credit scoring model highly depends on the accuracy and availability of the underlying data of the model as well as the corporate-wide information technology and the technical know-how for the development and maintenance of the algorithm. Nevertheless, credit scoring is predestinated for digitalization. Especially the cloud interfaces to external providers such as credit rating agencies worldwide and the possibility to use a wider range of information helps corporations to increase the predictability of a customer payment behavior and the minimization of credit risk.

The developed credit scoring model of Company XYZ for the small customers which is based on machine learning predictive statistics shows a high predictability accuracy in most countries of the region Europe, Middle East and Africa with exception of countries in South Europe, Middle East and Africa. Including country-level macroeconomic data might improve the model performance.

The literature review on the influence of macroeconomic effects on credit scoring model results and the country snapshots led to two main conclusions. Firstly, different studies proved the correlation of external effects on a customer's payment behavior and suggested the consideration of the factors within a scoring model. The fast-changing environment within a globalized world can have significant impact on a customer's payment behavior. Moreover, a list of important factors was identified.

Secondly, it supported the assumption of different sensitivities to economic effects among countries.

Both surveys conducted, with credit managers within Company XYZ and outside the company, support the findings of the literature review. The credit managers value the inclusion of macroeconomic aspects as important and would consider it up to 50% of the overall customer assessment. The indicators providing information on the direction of the economy and on financial markets are seen as most important with additional focus on oil and gas prices as well as commodity prices.

Even though the statistical analysis with the indicators oil price, unemployment rate, interest rate and consumer price index proved that macroeconomic indicators were not significant for each of the countries, significant correlations can be observed. Beck, Jakubík and Piloiu (2015) already pointed out that some countries are more related to changes in certain exchange rates or share prices than others depending on the countries' economies and financial as well as capital market (Beck, Jakubík, & Piloiu, 2015). This aligns for example with the statistical analysis of the oil price indicator. Countries with a higher oil dependency showed stronger correlations.

Overall, the thesis proved the importance of consideration of macroeconomic indicators within a credit scoring model. Nevertheless, due to the limitations of the analysis such as the short time range of the model and the correlated difficulty of the data availability of macroeconomic information, the specific choice of indicators needs to be tested once the model is based on a wider timer range. This especially needs a more sophisticated statistical approach done by experts in order to include aspects such as the time lag and test for non-linear relationships.

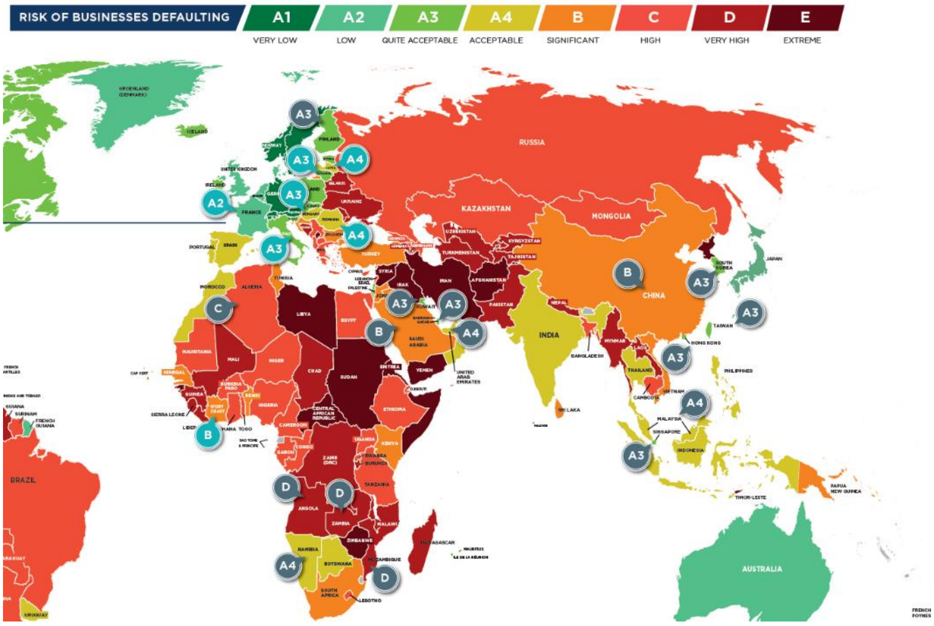
On top of that, there are some steps left until a final statement can be made on the improvement of the model predictability due to macro data. Once the choice of indicators is defined, an evaluation of the model predictability needs to be done for example with the help of a classification matrix. A comparison of the misclassification errors could finally lead to the result of whether the inclusion of macro data improves the credit scoring model of the Company XYZ.

9. Appendices

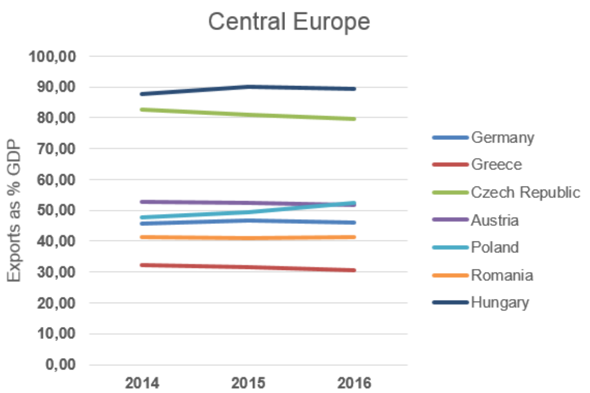
Appendix A: Types of transactions facing credit risk (Bouteillé & Coogan-Pushner, 2013, pp. 5-7)

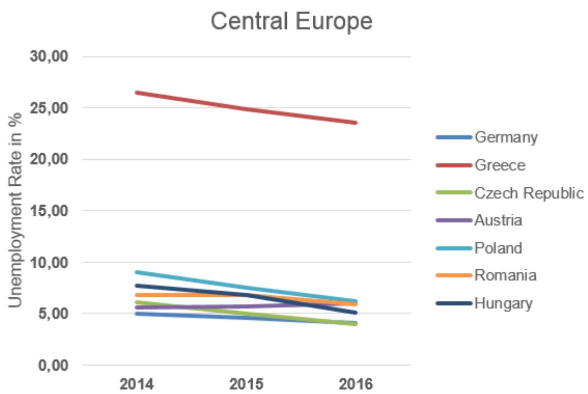
Credit Type	Losses Result From	Loss Type
Loaned money	Nonrepayment	Face amount
	Slow repayment	Time value of money
	Dispute/enforcement	Frictional costs
Lease obligation	Nonpayment	Recovery of asset, remarketing costs, difference in conditions
Receivables	Nonpayment of goods delivered or service performed	Face amount
Prepayment for goods or services	Nondelivery	Replacement cost
	Performance on delivery not as contracted	Incremental operating cost
	Slow delivery	Time value of money
	Dispute/enforcement	Frictional costs
Deposits	Nonrepayment	Face amount
		Time value of money
Claim or contingent claim on asset	Nonrepayment/Noncollection	Face amount
	Slow repayment/Slow collection	Time value of money
	Dispute/enforcement	Frictional costs
Derivative	Default of third party	Replacement cost (mark-to-market value)

Appendix B: Country risk map (Coface, 2016)

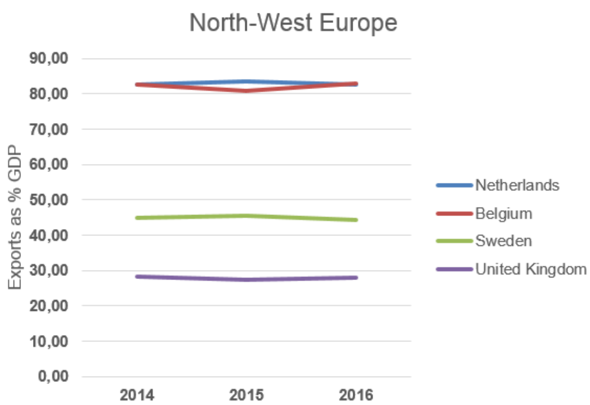


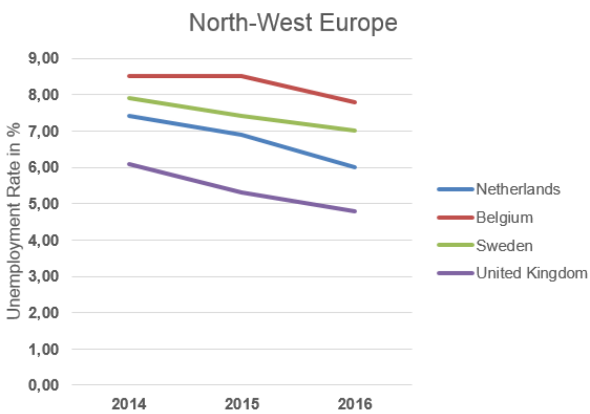
Appendix C: Exports as a % of GDP and Unemployment Rate of Central Europe (Passport Euromotior, 2014-2016)



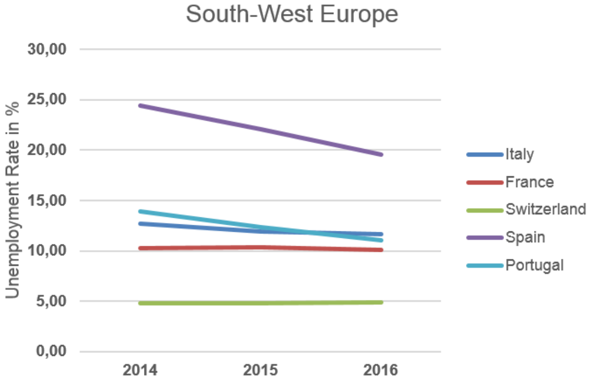


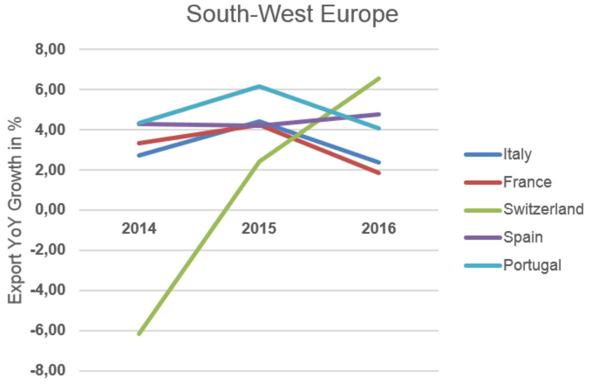
Appendix D: Exports as a % of GDP and Unemployment Rate of North-West Europe (Passport Euromotior, 2014-2016)



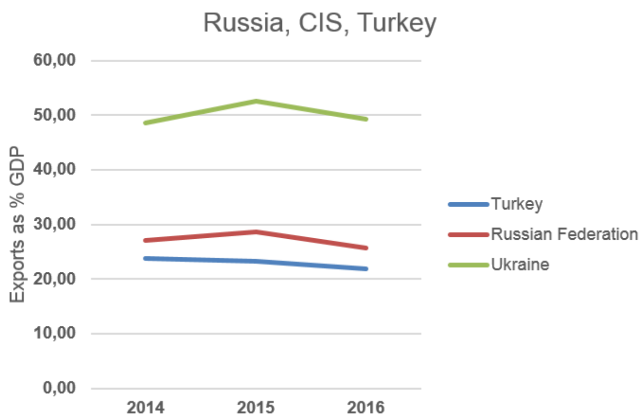


Appendix E: Unemployment Rate and Export YoY Growth of South-West Europe (Passport Euromotior, 2014-2016)

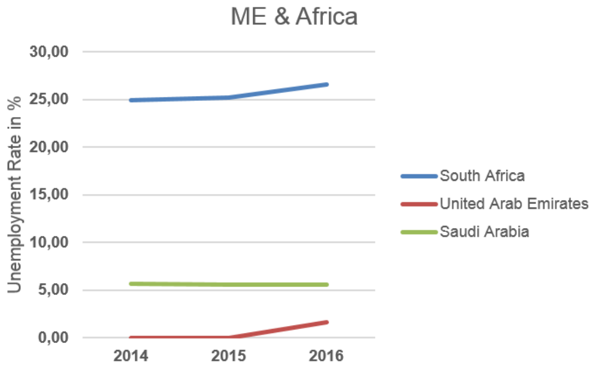


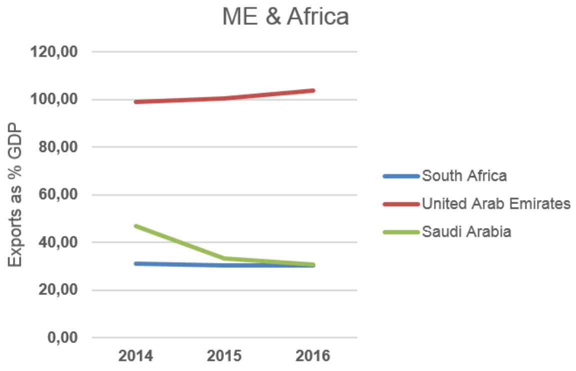


Appendix F: Exports as a % of GDP of Russia, CIS & Turkey (Passport Euromotior, 2014-2016)



Appendix G: Exports as a % of GDP and Unemployment Rate of Middle East & Africa (Passport Euromotior, 2014-2016)





Appendix H: Survey design (created by author)

1. Choose the industry that best describes your company:

2. In what country are you located?

3. On a scale of 1-10, how important are macroeconomic indicators for assessing customer credit risk? (1 = Very Important)

0 10

4. Does your company consider macroeconomic indicators when assessing customer risk?

- Yes
- Occasionally
- No

5. On average, what percentage of your credit risk assessment is based on macroeconomic indicators?

- Less than 5%
- 5% to 10%
- 11% to 20%
- 21% to 50%
- Greater than 50 %

* 6. What sources do you and your company use to learn about macroeconomic events and information? Choose all that apply:

- Company internal data
- International economic data and statistics organizations (OECD, IFS, Eurostat, World Bank)
- Governmental organizations
- Rating agencies
- Country-specific agencies (for example D&B)
- Trade Associations (e.g. FCIB)
- Trade credit insurance
- Newspapers and Journals
- Economic blogs and websites
- Other (please specify)

7. Rank the following three categories of macroeconomic data according to their importance in customer credit risk assessment. (1 = most important; 3 = least important)

- General Macroeconomic Conditions (Overall macroeconomic health)
- Direction of the Economy (Economic improvement or deterioration)
- Financial Market Conditions

	1	2	3
General Macroeconomic Conditions	○	○	○
Direction of the Economy	○	○	○
Financial Market Condition	○	○	○

* 8. General macroeconomic conditions include the following indicators. Please rank the **THREE** most important indicators from 1 (most important) to 3 (least important).

	1	2	3
Unemployment rate	○	○	○
Inflation (e.g. CPI)	○	○	○
(Real) GDP	○	○	○
Capacity utilization	○	○	○
Industrial production	○	○	○
Consumption indicators	○	○	○
Export and Import indicator	○	○	○
Corporate Insolvency Rate	○	○	○
Corporate Credit Share	○	○	○

* 9. Rank the following indicators for the Direction of the Economy in order of importance from 1 (most important) to 3 (least important).

	1	2	3
Real GDP growth	○	○	○
Growth of industrial production	○	○	○
Change in unemployment	○	○	○

* 10. The Financial Market Conditions include the following indicators. Please rank the three most important indicators from 1 (most important) to 3 (least important).

	1	2	3
Exchange rates	◯	◯	◯
Interest rates	◯	◯	◯
Stock market returns	◯	◯	◯
Stock market volatility	◯	◯	◯
Stock market indices	◯	◯	◯

11. Are there any additional indicators you would include in the previously mentioned categories, or with regard to your industry that have an effect on your customer's creditworthiness (e.g. a specific commodity price, oil price...)?

12. In your opinion, do your co-workers have the relevant skill set to consider macroeconomic indicators/effects when making credit risk assessments?

◯ Yes

◯ No

13. How would your company better support your credit analysts to ensure development of their knowledge and skills?

◯ Internal training

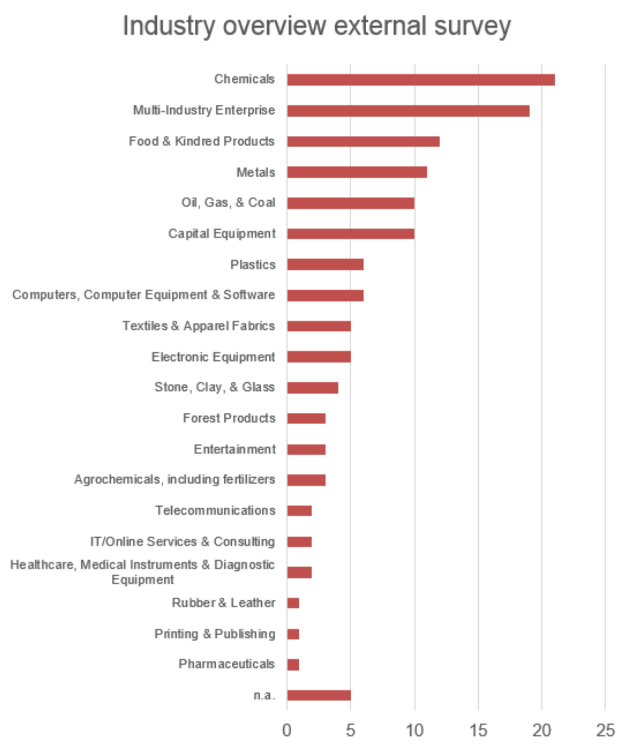
◯ External training

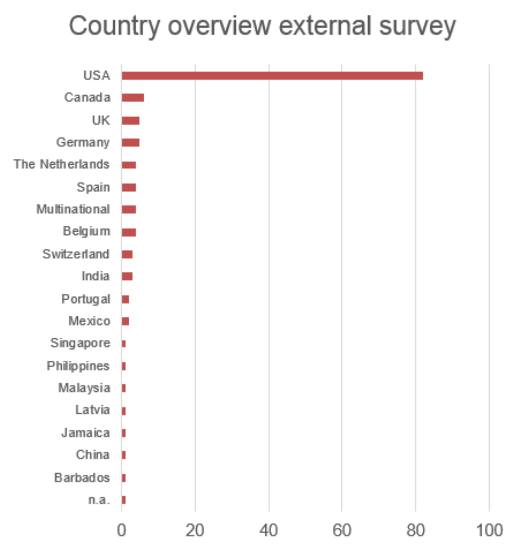
◯ Webinars

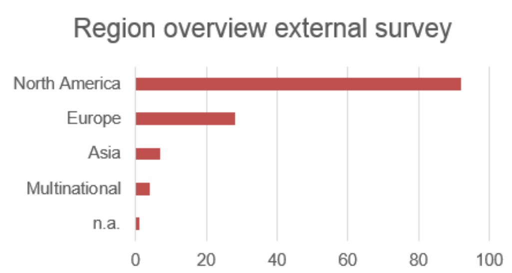
◯ Self-learning/-training (internet, literature)

◯ Other (please specify)

Appendix I: Sample population characteristics of external survey (created by author)







Appendix J: Overview of countries with statistically sufficient representation of customers (created by author)

Overview of countries with statistically sufficient representation of customers

Region	Country	Statistically sufficient repersentation of customers?
Benelux	LU	Sufficient
Benelux	NL	Sufficient
Benelux	BE	Sufficient
Central Asia	KG	Not sufficient
Central Asia	KZ	Sufficient
East Africa	BI	Not sufficient
East Africa	DJ	Not sufficient
East Africa	SC	Not sufficient
East Africa	YT	Not sufficient
East Africa	ER	Not sufficient
East Africa	RW	Not sufficient
East Africa	MG	Not sufficient
East Africa	ET	Not sufficient
East Africa	MU	Not sufficient
East Africa	RE	Sufficient
East Africa	UG	Sufficient
East Africa	TZ	Sufficient
East Africa	KE	Sufficient
East Europe	AM	Not sufficient
East Europe	GE	Not sufficient
East Europe	MD	Sufficient
East Europe	UA	Sufficient
EUC East	AL	Not sufficient
EUC East	ME	Not sufficient
EUC East	XK	Not sufficient
EUC East	CY	Sufficient
EUC East	MK	Sufficient
EUC East	BA	Sufficient
EUC East	HR	Sufficient
EUC East	RS	Sufficient
EUC East	BG	Sufficient
EUC East	SI	Sufficient
EUC East	RO	Sufficient
EUC East	HU	Sufficient
EUC East	GR	Sufficient
EUC North	PL	Sufficient
EUC West	SK	Sufficient
EUC West	CZ	Sufficient
EUC West	AT	Sufficient

Region	Country	Statistically sufficient repersentation of customers?
France	MC	Sufficient
France	FR	Sufficient
Germany	DE	Sufficient
Iberia	GI	Not sufficient
Iberia	XL	Not sufficient
Iberia	XC	Not sufficient
Iberia	AD	Not sufficient
Iberia	XA	Sufficient
Iberia	PT	Sufficient
Iberia	ES	Sufficient
Italy	SM	Sufficient
Italy	MT	Sufficient
Italy	IL	Sufficient
Italy	IT	Sufficient
Middle East & Egypt	PS	Not sufficient
Middle East & Egypt	SD	Not sufficient
Middle East & Egypt	SY	Not sufficient
Middle East & Egypt	YE	Not sufficient
Middle East & Egypt	IQ	Not sufficient
Middle East & Egypt	IR	Not sufficient
Middle East & Egypt	BH	Sufficient
Middle East & Egypt	LB	Sufficient
Middle East & Egypt	JO	Sufficient
Middle East & Egypt	KW	Sufficient
Middle East & Egypt	QA	Sufficient
Middle East & Egypt	OM	Sufficient
Middle East & Egypt	SA	Sufficient
Middle East & Egypt	EG	Sufficient
Middle East & Egypt	AE	Sufficient
Nordics & Baltics	GL	Not sufficient
Nordics & Baltics	FO	Sufficient
Nordics & Baltics	IS	Sufficient
Nordics & Baltics	EE	Sufficient
Nordics & Baltics	LV	Sufficient
Nordics & Baltics	NO	Sufficient
Nordics & Baltics	LT	Sufficient
Nordics & Baltics	FI	Sufficient
Nordics & Baltics	SE	Sufficient
Nordics & Baltics	DK	Sufficient

Region	Country	Statistically sufficient repersentation of customers?
Northwest Africa	GA	Not sufficient
Northwest Africa	GQ	Not sufficient
Northwest Africa	GN	Not sufficient
Northwest Africa	NE	Not sufficient
Northwest Africa	CV	Not sufficient
Northwest Africa	SN	Not sufficient
Northwest Africa	TG	Not sufficient
Northwest Africa	LY	Not sufficient
Northwest Africa	ML	Not sufficient
Northwest Africa	CM	Not sufficient
Northwest Africa	CI	Sufficient
Northwest Africa	TN	Sufficient
Northwest Africa	DZ	Sufficient
Northwest Africa	MA	Sufficient
Russia & Belarus	BY	Sufficient
Russia & Belarus	RU	Sufficient
Southern Africa	AO	Not sufficient
Southern Africa	BW	Not sufficient
Southern Africa	MW	Not sufficient
Southern Africa	SZ	Not sufficient
Southern Africa	MZ	Not sufficient
Southern Africa	ZW	Not sufficient
Southern Africa	ZM	Sufficient
Southern Africa	ZA	Sufficient
Southern Africa	NA	Sufficient
Switzerland	LI	Sufficient
Switzerland	CH	Sufficient
Turkey & Azerbaijan	AZ	Not sufficient
Turkey & Azerbaijan	TR	Sufficient
UK & Irland	QT	Not sufficient
UK & Irland	IE	Sufficient
UK & Irland	GB	Sufficient
West Africa	GM	Not sufficient
West Africa	CD	Not sufficient
West Africa	GH	Sufficient
West Africa	NG	Sufficient

Appendix K: Results of statistical analysis (created by author)

Country	Region	CPI r	CPI R²	CPI p-value	CPI Sign.
REGION	Benelux	-0,6718	0,4513	0,0167	Yes
Belgium	Benelux	-0,7745	0,5999	0,0031	Yes
Luxembourg	Benelux	0,8007	0,6411	0,0018	Yes
Netherlands	Benelux	0,8306	0,6898	0,0008	Yes
REGION	Central Asia	0,7037	0,4952	0,0107	Yes
Kazakhstan	Central Asia	0,7037	0,4952	0,0107	Yes
REGION	East Africa	0,7611	0,5792	0,0040	Yes
Kenya	East Africa	0,2168	0,0470	0,4985	No
Tanzania	East Africa	0,8115	0,6585	0,0014	Yes
Uganda	East Africa	0,2218	0,0492	0,4884	No
REGION	East Europe	-0,4468	0,1996	0,1454	No
Moldavia	East Europe	NA	NA	NA	No
Ukraine	East Europe	-0,4482	0,2009	0,1439	No
REGION	EUC East	0,2507	0,0628	0,4319	No
Bosnia-Herzegovina	EUC East	0,2858	0,0817	0,3678	No
Bulgaria	EUC East	0,7705	0,5937	0,0034	Yes
Croatia	EUC East	0,8164	0,6666	0,0012	Yes
Cyprus	EUC East	-0,2980	0,0888	0,3468	No
Greece	EUC East	-0,1216	0,0148	0,7066	No
Hungary	EUC East	0,1075	0,0115	0,7396	No
Romania	EUC East	-0,3110	0,0967	0,3251	No
Slovenia	EUC East	-0,1366	0,0187	0,6721	No
REGION	EUC North	0,6719	0,4515	0,0167	Yes
Poland	EUC North	0,6719	0,4515	0,0167	Yes
REGION	EUC West	0,4520	0,2043	0,1401	No
Austria	EUC West	0,4606	0,2121	0,1319	No
CzechRepublic	EUC West	-0,1973	0,0389	0,5387	No
Slovakia	EUC West	0,6574	0,4322	0,0202	Yes
REGION	France	0,3230	0,1044	0,3058	No
France	France	0,3230	0,1044	0,3058	No
REGION	Germany	0,0495	0,0024	0,8786	No
Germany	Germany	0,0495	0,0024	0,8786	No
REGION	Iberia	0,2200	0,0484	0,4920	No
Portugal	Iberia	0,7961	0,6338	0,0019	Yes
Spain	Iberia	0,1797	0,0323	0,5764	No
REGION	Italy	0,9117	0,8313	0,0000	Yes
Israel	Italy	-0,0336	0,0011	0,9174	No
Italy	Italy	0,9107	0,8293	0,0000	Yes
Malta	Italy	0,8858	0,7847	0,0001	Yes

Country	Region	CPI r	CPI R²	CPI p-value	CPI Sign.
REGION	Middle East & Egypt	0,0462	0,0021	0,8867	No
Bahrain	Middle East & Egypt	0,7736	0,5984	0,0032	Yes
Egypt	Middle East & Egypt	0,8305	0,6898	0,0008	Yes
Jordan	Middle East & Egypt	0,2407	0,0579	0,4511	No
Qatar	Middle East & Egypt	-0,4073	0,1659	0,1888	No
Saudi Arabia	Middle East & Egypt	-0,8624	0,7437	0,0003	Yes
UAE	Middle East & Egypt	-0,6616	0,4377	0,0191	Yes
REGION	Nordics & Baltics	-0,8547	0,7304	0,0004	Yes
Denmark	Nordics & Baltics	0,6766	0,4578	0,0157	Yes
Estonia	Nordics & Baltics	-0,0592	0,0035	0,8551	No
Finland	Nordics & Baltics	-0,6285	0,3950	0,0286	Yes
Latvia	Nordics & Baltics	-0,7336	0,5381	0,0066	Yes
Lithuania	Nordics & Baltics	-0,4298	0,1847	0,1632	No
Norway	Nordics & Baltics	-0,9691	0,9392	0,0000	Yes
Sweden	Nordics & Baltics	-0,3310	0,1096	0,2932	No
REGION	Northwest Africa	0,6469	0,4184	0,0230	Yes
Algeria	Northwest Africa	0,5753	0,3310	0,0503	No
Morocco	Northwest Africa	-0,0852	0,0073	0,7923	No
Tunisia	Northwest Africa	0,8702	0,7572	0,0002	Yes
REGION	Russia & Belarus	0,3341	0,1116	0,2885	No
Belarus	Russia & Belarus	-0,1966	0,0387	0,5402	No
Russia	Russia & Belarus	0,5694	0,3242	0,0533	No
REGION	Southern Africa	-0,8802	0,7748	0,0002	Yes
Namibia	Southern Africa	-0,8793	0,7731	0,0002	Yes
South Africa	Southern Africa	-0,8182	0,6694	0,0011	Yes
Zambia	Southern Africa	0,8324	0,6928	0,0008	Yes
REGION	Switzerland	-0,9070	0,8227	0,0000	Yes
Switzerland	Switzerland	-0,9070	0,8227	0,0000	Yes
REGION	Turkey & Azerbaijan	0,2411	0,0581	0,4504	No
Turkey	Turkey & Azerbaijan	0,2411	0,0581	0,4504	No
REGION	UK & Irland	-0,8480	0,7191	0,0005	Yes
Ireland	UK & Irland	-0,3294	0,1085	0,2958	No
UK	UK & Irland	-0,8424	0,7096	0,0006	Yes
REGION	West Africa	0,8654	0,7489	0,0003	Yes
Ghana	West Africa	-0,5063	0,2564	0,0930	No
Nigeria	West Africa	0,7943	0,6310	0,0020	Yes

	Intercept			Slope CPI
Country[T.Bahrain]	0,412064		CPI:Country[T.Bahrain]	0,060199
Country[T.Belgium]	0,207786		CPI:Country[T.Belgium]	-0,009986
Country[T.Bulgaria]	0,241448		CPI:Country[T.Bulgaria]	0,021315
Country[T.Croatia]	0,333782		CPI:Country[T.Croatia]	0,053571
Country[T.Denmark]	0,092900		CPI:Country[T.Denmark]	0,045553
Country[T.Egypt]	0,237433		CPI:Country[T.Egypt]	0,009682
Country[T.Finland]	0,095539		CPI:Country[T.Finland]	-0,043630
Country[T.Italy]	0,234927		CPI:Country[T.Italy]	0,045137
Country[T.Kazakhatan]	0,214237		CPI:Country[T.Kazakhatan]	0,006215
Country[T.Latvia]	0,115003		CPI:Country[T.Latvia]	-0,027324
Country[T.Luxembourg]	0,096492		CPI:Country[T.Luxembourg]	0,049043
Country[T.Malta]	0,044311		CPI:Country[T.Malta]	0,156785
Country[T.Namibia]	0,236372		CPI:Country[T.Namibia]	-0,007235
Country[T.Netherlands]	0,185618		CPI:Country[T.Netherlands]	0,022887
Country[T.Nigeria]	0,057863		CPI:Country[T.Nigeria]	0,018122
Country[T.Norway]	0,255857		CPI:Country[T.Norway]	-0,044259
Country[T.Poland]	0,110420		CPI:Country[T.Poland]	0,023956
Country[T.Portugal]	0,274756		CPI:Country[T.Portugal]	0,039897
Country[T.Saudi Arabia]	0,549064		CPI:Country[T.Saudi Arabia]	-0,038729
Country[T.Slovakia]	0,261381		CPI:Country[T.Slovakia]	0,066607
Country[T.South Africa]	0,235901		CPI:Country[T.South Africa]	-0,011626
Country[T.Switzerland]	0,112014		CPI:Country[T.Switzerland]	-0,025692
Country[T.Tanzania]	-0,160703		CPI:Country[T.Tanzania]	0,098816
Country[T.Tunisia]	0,076432		CPI:Country[T.Tunisia]	0,066629
Country[T.UAE]	0,589204		CPI:Country[T.UAE]	-0,005699
Country[T.UK]	0,195809		CPI:Country[T.UK]	-0,082070
Country[T.Zambia]	0,298018		CPI:Country[T.Zambia]	0,008446

Interest Rate

Country	Region	r	R²	p-value	Sign.
REGION	**Benelux**	**0,9138**	**0,8350**	**0,0000**	**Yes**
Belgium	Benelux	0,8811	0,7763	0,0002	Yes
Luxembourg	Benelux	0,7251	0,5258	0,0076	Yes
Netherlands	Benelux	0,8690	0,7552	0,0002	Yes
REGION	**EUC East**	**0,9221**	**0,8502**	**0,0000**	**Yes**
Cyprus	EUC East	-0,6603	0,4360	0,0194	Yes
Greece	EUC East	0,8594	0,7386	0,0003	Yes
Hungary	EUC East	0,8808	0,7757	0,0002	Yes
Slovenia	EUC East	0,8236	0,6783	0,0010	Yes
REGION	**EUC North**	**0,4157**	**0,1728**	**0,1790**	**No**
Poland	EUC North	0,4157	0,1728	0,1790	No
REGION	**EUC West**	**0,8920**	**0,7957**	**0,0001**	**Yes**
Austria	EUC West	0,8855	0,7841	0,0001	Yes
Slovakia	EUC West	0,8783	0,7715	0,0002	Yes
REGION	**France**	**0,8862**	**0,7853**	**0,0001**	**Yes**
France	France	0,8862	0,7853	0,0001	Yes
REGION	**Germany**	**0,9277**	**0,8607**	**0,0000**	**Yes**
Germany	Germany	0,9277	0,8607	0,0000	Yes
REGION	**Iberia**	**0,2990**	**0,0894**	**0,3452**	**No**
Portugal	Iberia	0,5585	0,3120	0,0591	No
Spain	Iberia	0,2408	0,0580	0,4509	No
REGION	**Italy**	**0,8942**	**0,7996**	**0,0001**	**Yes**
Israel	Italy	-0,4060	0,1648	0,1903	No
Italy	Italy	0,8926	0,7967	0,0001	Yes
Malta	Italy	0,8484	0,7197	0,0005	Yes

Interest Rate

Country	Region	r	R²	p-value	Sign.
REGION	**Middle East & Egypt**	**0,7310**	**0,5344**	**0,0069**	**Yes**
Bahrain	Middle East & Egypt	0,7485	0,5602	0,2245	No
Egypt	Middle East & Egypt	0,8513	0,7247	0,0004	Yes
Oman	Middle East & Egypt	0,7107	0,5051	0,3689	No
Qatar	Middle East & Egypt	0,7435	0,5527	0,2759	No
Saudi Arabia	Middle East & Egypt	0,7074	0,5004	0,4984	No
UAE	Middle East & Egypt	0,7048	0,4967	0,0300	Yes
REGION	**Nordics & Baltics**	**0,9003**	**0,8106**	**0,0001**	**Yes**
Estonia	Nordics & Baltics	0,7480	0,5594	0,0052	Yes
Finland	Nordics & Baltics	0,8357	0,6985	0,0007	Yes
Iceland	Nordics & Baltics	0,1216	0,0148	0,7067	No
Latvia	Nordics & Baltics	-0,7419	0,5505	0,0057	Yes
Lithuania	Nordics & Baltics	0,3978	0,1582	0,2003	No
Norway	Nordics & Baltics	0,9072	0,8230	0,0000	Yes
Sweden	Nordics & Baltics	0,4636	0,2149	0,1290	No
REGION	**Russia & Belarus**	**0,7097**	**0,5037**	**0,0097**	**Yes**
Russia	Russia & Belarus	0,7097	0,5037	0,0097	Yes
REGION	**Southern Africa**	**-0,7939**	**0,6302**	**0,0020**	**Yes**
South Africa	Southern Africa	-0,7939	0,6302	0,0020	Yes
REGION	Switzerland	0,1386	0,0192	0,6676	No
Switzerland	Switzerland	0,1386	0,0192	0,6676	No
REGION	**Turkey & Azerbaijan**	**-0,2114**	**0,0447**	**0,5096**	**No**
Turkey	Turkey & Azerbaijan	-0,2114	0,0447	0,5096	No
REGION	**UK & Irland**	**0,3525**	**0,1242**	**0,2611**	**No**
Ireland	UK & Irland	0,9172	0,8413	0,0000	Yes
United Kingdom	UK & Irland	0,1837	0,0337	0,5677	No

	Intercept			Slope IR
Country[T.Austria]	**0,05214**		IR:Country[T.Austria]	**0,0456262**
Country[T.Belgium]	**0,20542**		IR:Country[T.Belgium]	**0,056661388**
Country[T.Cyprus]	**0,35390**		IR:Country[T.Cyprus]	**-0,272914305**
Country[T.Egypt]	**0,18141**		IR:Country[T.Egypt]	**0,016063959**
Country[T.Estonia]	**0,14431**		IR:Country[T.Estonia]	**0,094320383**
Country[T.Finland]	**0,11022**		IR:Country[T.Finland]	**0,076930376**
Country[T.France]	**0,15935**		IR:Country[T.France]	**0,072780737**
Country[T.Germany]	**0,05509**		IR:Country[T.Germany]	**0,044230971**
Country[T.Greece]	**0,47086**		IR:Country[T.Greece]	**0,295040153**
Country[T.Hungary]	**0,00669**		IR:Country[T.Hungary]	**0,040234052**
Country[T.Ireland]	**0,34412**		IR:Country[T.Ireland]	**0,134345746**
Country[T.Italy]	**0,26019**		IR:Country[T.Italy]	**0,11474806**
Country[T.Latvia]	**0,10344**		IR:Country[T.Latvia]	**-0,087878858**
Country[T.Luxembourg]	**0,14891**		IR:Country[T.Luxembourg]	**0,140205975**
Country[T.Malta]	**0,30936**		IR:Country[T.Malta]	**0,356887937**
Country[T.Netherlands]	**0,21166**		IR:Country[T.Netherlands]	**0,065139302**
Country[T.Norway]	**-0,11216**		IR:Country[T.Norway]	**0,143249009**
Country[T.Russia]	**-0,01241**		IR:Country[T.Russia]	**0,01452247**
Country[T.Slovakia]	**0,26361**		IR:Country[T.Slovakia]	**0,152072529**
Country[T.Slovenia]	**0,22826**		IR:Country[T.Slovenia]	**0,195879715**
Country[T.South Africa]	**0,30768**		IR:Country[T.South Africa]	**-0,021274024**
Country[T.UAE]	**0,52665**		IR:Country[T.UAE]	**NA**

Oil Price

Country	Region	r	R²	p-value	Sign.
REGION	**Benelux**	**0,3859**	**0,1489**	**0,2154**	**No**
Belgium	Benelux	0,2498	0,0624	0,4337	No
Luxembourg	Benelux	0,6250	0,3907	0,0298	Yes
Netherlands	Benelux	0,5095	0,2596	0,0907	No
REGION	**Central Asia**	**-0,7716**	**0,5954**	**0,0033**	**Yes**
Kazakhstan	Central Asia	-0,7716	0,5954	0,0033	Yes
REGION	**East Africa**	**0,4034**	**0,1628**	**0,1934**	**No**
Kenya	East Africa	-0,7520	0,5655	0,0048	Yes
Réunion	East Africa	0,8011	0,6417	0,0017	Yes
Tanzania	East Africa	0,4598	0,2115	0,1325	No
Uganda	East Africa	0,6398	0,4094	0,0250	Yes
REGION	**East Europe**	**0,0726**	**0,0053**	**0,8227**	**No**
Moldavia	East Europe	NA	NA	NA	No
Ukraine	East Europe	0,0726	0,0053	0,8227	No
REGION	**EUC East**	**0,4339**	**0,1882**	**0,1588**	**No**
Bosnia-Herzegovina	EUC East	0,3893	0,1515	0,2110	No
Bulgaria	EUC East	-0,0423	0,0018	0,8962	No
Croatia	EUC East	0,4550	0,2071	0,1372	No
Cyprus	EUC East	-0,3302	0,1090	0,2946	No
Greece	EUC East	0,4184	0,1751	0,1758	No
Hungary	EUC East	0,6164	0,3800	0,0328	Yes
Macedonia	EUC East	0,4356	0,1898	0,1569	No
Romania	EUC East	-0,5572	0,3105	0,0598	No
Serbia	EUC East	-0,2868	0,0822	0,3662	No
Slovenia	EUC East	0,7331	0,5375	0,0067	Yes
REGION	**EUC North**	**0,5552**	**0,3082**	**0,0610**	**No**
Poland	EUC North	0,5552	0,3082	0,0610	No
REGION	**EUC West**	**0,3694**	**0,1365**	**0,2373**	**No**
Austria	EUC West	0,4829	0,2332	0,1118	No
Czech Republic	EUC West	-0,3151	0,0993	0,3185	No
Slovakia	EUC West	0,3336	0,1113	0,2893	No
REGION	**France**	**0,7849**	**0,6161**	**0,0025**	**Yes**
France	France	0,7912	0,6261	0,0022	Yes
Monaco	France	0,2366	0,0560	0,4591	No
REGION	**Germany**	**0,5550**	**0,3081**	**0,0610**	**No**
Germany	Germany	0,5550	0,3081	0,0610	No
REGION	**Iberia**	**-0,1090**	**0,0119**	**0,7360**	**No**
Portugal	Iberia	0,6439	0,4146	0,0238	Yes
Spain	Iberia	-0,1603	0,0257	0,6188	No
Canary Islands	Iberia	-0,8039	0,6462	0,0016	Yes
REGION	**Italy**	**0,5109**	**0,2610**	**0,0896**	**No**
Israel	Italy	-0,3860	0,1490	0,2152	No
Italy	Italy	0,5084	0,2585	0,0915	No
Malta	Italy	0,7459	0,5564	0,0053	Yes
San Marino	Italy	0,4160	0,1731	0,1786	No

Oil Price

Country	Region	r	R²	p-value	Sign.
REGION	**Middle East & Egypt**	**-0,7448**	**0,5547**	**0,0055**	**Yes**
Bahrain	Middle East & Egypt	-0,7753	0,6011	0,0030	Yes
Egypt	Middle East & Egypt	-0,6258	0,3916	0,0295	Yes
Jordan	Middle East & Egypt	-0,4281	0,1832	0,1651	No
Kuwait	Middle East & Egypt	-0,6599	0,4355	0,0195	Yes
Lebanon	Middle East & Egypt	-0,8634	0,7454	0,0003	Yes
Oman	Middle East & Egypt	-0,6767	0,4579	0,0157	Yes
Qatar	Middle East & Egypt	0,4694	0,2203	0,1237	No
Saudi Arabia	Middle East & Egypt	0,7878	0,6206	0,0023	Yes
UAE	Middle East & Egypt	-0,7613	0,5796	0,0040	Yes
REGION	**Nordics & Baltics**	**0,6956**	**0,4839**	**0,0120**	**Yes**
Denmark	Nordics & Baltics	0,7867	0,6189	0,0024	Yes
Estonia	Nordics & Baltics	0,5139	0,2641	0,0875	No
Faroe Islands	Nordics & Baltics	0,5561	0,3093	0,0604	No
Finland	Nordics & Baltics	0,6624	0,4387	0,0189	Yes
Iceland	Nordics & Baltics	-0,0792	0,0063	0,8067	No
Latvia	Nordics & Baltics	-0,8544	0,7300	0,0004	Yes
Lithuania	Nordics & Baltics	0,6135	0,3764	0,0339	Yes
Norway	Nordics & Baltics	0,7052	0,4972	0,0104	Yes
Sweden	Nordics & Baltics	-0,2548	0,0649	0,4242	No
REGION	**Northwest Africa**	**-0,7203**	**0,5188**	**0,0082**	**Yes**
Algeria	Northwest Africa	-0,7997	0,6395	0,0018	Yes
Ivory Coast	Northwest Africa	-0,8327	0,6933	0,0008	Yes
Morocco	Northwest Africa	-0,7863	0,6183	0,0024	Yes
Tunisia	Northwest Africa	0,9282	0,8616	0,0000	Yes
REGION	**Russia & Belarus**	**0,0007**	**0,0000**	**0,9983**	**No**
Belarus	Russia & Belarus	-0,3372	0,1137	0,2837	No
Russia	Russia & Belarus	0,2099	0,0440	0,5127	No
REGION	**Southern Africa**	**0,4173**	**0,1742**	**0,1771**	**No**
Namibia	Southern Africa	0,4055	0,1644	0,1909	No
South Africa	Southern Africa	0,7461	0,5567	0,0053	Yes
Zambia	Southern Africa	-0,8754	0,7663	0,0002	Yes
REGION	**Switzerland**	**0,5868**	**0,3443**	**0,0449**	**Yes**
Liechtenstein	Switzerland	0,0946	0,0089	0,7700	No
Switzerland	Switzerland	0,6006	0,3607	0,0389	Yes
REGION	**Turkey & Azerbaijan**	**-0,7612**	**0,5794**	**0,0040**	**Yes**
Turkey	Turkey & Azerbaijan	-0,7612	0,5794	0,0040	Yes
REGION	**UK & Irland**	**0,6704**	**0,4495**	**0,0170**	**Yes**
Ireland	UK & Irland	0,5815	0,3382	0,0473	Yes
United Kingdom	UK & Irland	0,6745	0,4549	0,0161	Yes
REGION	**West Africa**	**-0,7391**	**0,5462**	**0,0060**	**Yes**
Ghana	West Africa	0,3271	0,1070	0,2993	No
Nigeria	West Africa	-0,7851	0,6164	0,0025	Yes

	Intercept			Slope Oil Price
Country[T.Algeria]	**0,3839445**		Oil_Price:Country[T.Algeria]	**-0,0018828**
Country[T.Bahrain]	**1,0708344**		Oil_Price:Country[T.Bahrain]	**-0,0093638**
Country[T.Canary Islands]	**0,7773483**		Oil_Price:Country[T.Canary Islands]	**-0,0077424**
Country[T.Denmark]	**0,0084440**		Oil_Price:Country[T.Denmark]	**0,0018087**
Country[T.Egypt]	**0,4389997**		Oil_Price:Country[T.Egypt]	**-0,0018621**
Country[T.Finland]	**0,0363758**		Oil_Price:Country[T.Finland]	**0,0010153**
Country[T.France]	**0,0827680**		Oil_Price:Country[T.France]	**0,0010821**
Country[T.Hungary]	**-0,0237955**		Oil_Price:Country[T.Hungary]	**0,0019064**
Country[T.Ireland]	**0,2347821**		Oil_Price:Country[T.Ireland]	**0,0014184**
Country[T.Ivory Coast]	**0,7578335**		Oil_Price:Country[T.Ivory Coast]	**-0,0094154**
Country[T.Kazakhatan]	**0,5784218**		Oil_Price:Country[T.Kazakhatan]	**-0,0052418**
Country[T.Kenya]	**0,6980880**		Oil_Price:Country[T.Kenya]	**-0,0034592**
Country[T.Kuwait]	**1,0923363**		Oil_Price:Country[T.Kuwait]	**-0,0087023**
Country[T.Latvia]	**0,2168455**		Oil_Price:Country[T.Latvia]	**-0,0016852**
Country[T.Lebanon]	**0,5940415**		Oil_Price:Country[T.Lebanon]	**-0,0078078**
Country[T.Lithuania]	**0,0372095**		Oil_Price:Country[T.Lithuania]	**0,0014503**
Country[T.Luxembourg]	**0,0053772**		Oil_Price:Country[T.Luxembourg]	**0,0020125**
Country[T.Malta]	**-0,0616879**		Oil_Price:Country[T.Malta]	**0,0052255**
Country[T.Morocco]	**0,5576574**		Oil_Price:Country[T.Morocco]	**-0,0030909**
Country[T.Nigeria]	**0,6535882**		Oil_Price:Country[T.Nigeria]	**-0,0070665**
Country[T.Norway]	**-0,0304644**		Oil_Price:Country[T.Norway]	**0,0029480**
Country[T.Oman]	**0,9920952**		Oil_Price:Country[T.Oman]	**-0,0027643**
Country[T.Portugal]	**0,2520715**		Oil_Price:Country[T.Portugal]	**0,0008293**
Country[T.Réunion]	**-0,3333058**		Oil_Price:Country[T.Réunion]	**0,0106739**
Country[T.Saudi Arabia]	**0,2846837**		Oil_Price:Country[T.Saudi Arabia]	**0,0035170**
Country[T.Slovenia]	**0,0226418**		Oil_Price:Country[T.Slovenia]	**0,0029036**
Country[T.South Africa]	**0,0951403**		Oil_Price:Country[T.South Africa]	**0,0013712**
Country[T.Switzerland]	**0,0789799**		Oil_Price:Country[T.Switzerland]	**0,0010775**
Country[T.Tunisia]	**0,0738209**		Oil_Price:Country[T.Tunisia]	**0,0047064**
Country[T.Turkey]	**0,3223234**		Oil_Price:Country[T.Turkey]	**-0,0013171**
Country[T.UAE]	**0,6391717**		Oil_Price:Country[T.UAE]	**-0,0012098**
Country[T.Uganda]	**0,0380562**		Oil_Price:Country[T.Uganda]	**0,0073176**
Country[T.United Kingdom]	**0,0697476**		Oil_Price:Country[T.United Kingdom]	**0,0019828**
Country[T.Zambia]	**0,9078335**		Oil_Price:Country[T.Zambia]	**-0,0083798**

Unemployment Rate

Country	Region	r	R²	p-value	Sign
REGION	**Benelux**	**0,5426**	**0,2944**	**0,0683**	**No**
Belgium	Benelux	0,2522	0,0636	0,4290	No
Luxembourg	Benelux	0,4842	0,2344	0,1107	No
Netherlands	Benelux	0,8852	0,7837	0,0001	Yes
REGION	**Central Asia**	**0,7981**	**0,6369**	**0,0019**	**Yes**
Central Asia	Kazakhstan	0,7981	0,6369	0,0019	Yes
REGION	**East Europe**	**NA**	**NA**	**NA**	**No**
Moldavia	East Europe	NA	NA	NA	No
REGION	**EUC East**	**0,9355**	**0,8752**	**0,0000**	**Yes**
Bulgaria	EUC East	0,1725	0,0297	0,5920	No
Croatia	EUC East	0,5166	0,2668	0,0855	No
Cyprus	EUC East	-0,6738	0,4539	0,0163	Yes
Greece	EUC East	0,8506	0,7236	0,0005	Yes
Hungary	EUC East	0,9501	0,9027	0,0000	Yes
Romania	EUC East	-0,1306	0,0171	0,6858	No
Slovenia	EUC East	0,7151	0,5114	0,0089	Yes
REGION	**EUC West**	**0,3719**	**0,1383**	**0,2339**	**No**
Austria	EUC West	-0,8329	0,6937	0,0008	Yes
Czech Republic	EUC West	-0,3108	0,0966	0,3255	No
Slovakia	EUC West	0,8630	0,7448	0,0003	Yes
REGION	**France**	**0,9233**	**0,8526**	**0,0000**	**Yes**
France	France	0,9233	0,8526	0,0000	Yes
REGION	**Germany**	**0,9288**	**0,8626**	**0,0000**	**Yes**
Germany	Germany	0,9288	0,8626	0,0000	Yes

Unemployment Rate

Country	Region	r	R²	p-value	Sign
REGION	**Iberia**	**0,2152**	**0,0463**	**0,5017**	**No**
Portugal	Iberia	0,6060	0,3672	0,0367	Yes
Spain	Iberia	0,1000	0,0100	0,7572	No
REGION	**Italy**	**-0,3714**	**0,1380**	**0,2345**	**No**
Israel	Italy	-0,5174	0,2677	0,0849	No
Italy	Italy	-0,4476	0,2003	0,1446	No
Malta	Italy	0,8422	0,7092	0,0006	Yes
REGION	**Nordics & Baltics**	**0,8738**	**0,7636**	**0,0002**	**Yes**
Denmark	Nordics & Baltics	-0,1656	0,0274	0,6069	No
Estonia	Nordics & Baltics	-0,5891	0,3470	0,0439	Yes
Finland	Nordics & Baltics	0,8116	0,6588	0,0013	Yes
Iceland	Nordics & Baltics	-0,7124	0,5076	0,0093	Yes
Latvia	Nordics & Baltics	-0,5198	0,2702	0,0832	No
Lithuania	Nordics & Baltics	0,4743	0,2249	0,1193	No
Norway	Nordics & Baltics	-0,7076	0,5007	0,0100	Yes
Sweden	Nordics & Baltics	0,3405	0,1160	0,2788	No
REGION	**Russia & Belarus**	**-0,0558**	**0,0031**	**0,8632**	**No**
Russia	Russia & Belarus	-0,0558	0,0031	0,8632	No
REGION	**Switzerland**	**-0,5987**	**0,3585**	**0,0397**	**Yes**
Switzerland	Switzerland	-0,5987	0,3585	0,0397	Yes
REGION	**Turkey & Azerbaijan**	**-0,5601**	**0,3137**	**0,0582**	**No**
Turkey	Turkey & Azerbaijan	-0,5601	0,3137	0,0582	No
REGION	**UK & Irland**	**0,9522**	**0,9066**	**0,0000**	**Yes**
Ireland	UK & Irland	0,8665	0,7508	0,0003	Yes
United Kingdom	UK & Irland	0,9116	0,8310	0,0000	Yes

	Intercept			Slope UR
Country[T.Austria]	0,176507		UR:Country[T.Austria]	-0,02279
Country[T.Cyprus]	0,908068		UR:Country[T.Cyprus]	-0,03651
Country[T.Estonia]	0,232472		UR:Country[T.Estonia]	-0,01769
Country[T.Finland]	-0,30533		UR:Country[T.Finland]	0,043323
Country[T.France]	-0,50235		UR:Country[T.France]	0,063077
Country[T.Germany]	-0,11056		UR:Country[T.Germany]	0,035336
Country[T.Greece]	-1,20127		UR:Country[T.Greece]	0,066406
Country[T.Hungary]	-0,12941		UR:Country[T.Hungary]	0,035369
Country[T.Iceland]	0,616978		UR:Country[T.Iceland]	-0,16355
Country[T.Ireland]	-0,01212		UR:Country[T.Ireland]	0,037217
Country[T.Kazakhatan]	-2,199		UR:Country[T.Kazakhatan]	0,497512
Country[T.Malta]	-0,74952		UR:Country[T.Malta]	0,193424
Country[T.Netherlands]	-0,00614		UR:Country[T.Netherlands]	0,030886
Country[T.Norway]	0,815966		UR:Country[T.Norway]	-0,14776
Country[T.Portugal]	0,15673		UR:Country[T.Portugal]	0,011783
Country[T.Slovakia]	-0,07894		UR:Country[T.Slovakia]	0,029039
Country[T.Slovenia]	-0,26011		UR:Country[T.Slovenia]	0,052568
Country[T.Switzerland]	0,665672		UR:Country[T.Switzerland]	-0,16095
Country[T.United Kingdom]	-0,33035		UR:Country[T.United Kingdom]	0,099141

Appendix L: Oil rents as a % of GDP (The World Bank, n.d.)

Oil Rents as % of GDP

Country	Region	2014	2015	2016
Belgium	Benelux	0,0	0,0	0,0
Luxembourg	Benelux	0,0	0,0	0,0
Netherlands	Benelux	0,1	0,1	0,0
Kazakhstan	Central Asia	12,1	11,3	5,6
Kenya	East Africa	0,0	0,0	0,0
Ukraine	East Europe	0,5	0,5	0,3
Bosnia-Herzegovina	EUC East	0,0	0,0	0,0
Bulgaria	EUC East	0,0	0,0	0,0
Croatia	EUC East	0,3	0,3	0,1
Cyprus	EUC East	0,0	0,0	0,0
Greece	EUC East	0,0	0,0	0,0
Hungary	EUC East	0,2	0,2	0,1
Romania	EUC East	0,9	0,7	0,3
Serbia	EUC East	0,3	0,2	0,1
Slovenia	EUC East	0,0	0,0	..
Poland	EUC North	0,1	0,1	0,0
Austria	EUC West	0,1	0,1	0,0
Czech Republic	EUC West	0,0	0,0	0,0
Slovakia	EUC West	0,0	0,0	0,0
France	France	0,0	0,0	0,0
Germany	Germany	0,0	0,0	0,0
Portugal	Iberia	0,0	0,0	0,0
Spain	Iberia	0,0	0,0	0,0
Israel	Italy	0,0	0,0	0,0
Italy	Italy	0,1	0,1	0,0
Malta	Italy	0,0	0,0	0,0
Bahrain	Middle East & Egypt	4,5	4,5	2,6
Egypt	Middle East & Egypt	7,0	5,9	2,6
Jordan	Middle East & Egypt	0,0	0,0	0,0

* grey highlighted countries have significant correlations

Oil Rents as % of GDP

Country	Region	2014	2015	2016
Kuwait	Middle East & Egypt	56,1	53,4	38,5
Lebanon	Middle East & Egypt	0,0	0,0	0,0
Oman	Middle East & Egypt	39,9	35,3	20,5
Qatar	Middle East & Egypt	12,2	10,4	5,9
Saudi Arabia	Middle East & Egypt	42,9	38,9	22,5
UAE	Middle East & Egypt	24,0	21,4	11,2
Denmark	Nordics & Baltics	1,0	0,8	0,4
Estonia	Nordics & Baltics	0,3	0,2	0,1
Finland	Nordics & Baltics	0,0	0,0	0,0
Iceland	Nordics & Baltics	0,0	0,0	0,0
Latvia	Nordics & Baltics	0,0	0,0	0,0
Lithuania	Nordics & Baltics	0,1	0,1	0,0
Norway	Nordics & Baltics	5,7	5,5	3,0
Sweden	Nordics & Baltics	0,0	0,0	0,0
Algeria	Northwest Africa	17,4	15,7	9,1
Ivory Coast	Northwest Africa	2,0	1,1	0,4
Morocco	Northwest Africa	0,0	0,0	0,0
Tunisia	Northwest Africa	4,4	3,4	1,8
Belarus	Russia & Belarus	0,7	0,5	0,3
Russia	Russia & Belarus	9,2	8,8	5,6
Namibia	Southern Africa	0,0	0,0	0,0
South Africa	Southern Africa	0,0	0,0	0,0
Zambia	Southern Africa	0,0	0,0	0,0
Switzerland	Switzerland	0,0	0,0	0,0
Turkey	Turkey & Azerbaijan	0,1	0,1	0,0
Ireland	UK & Irland	0,0	0,0	0,0
United Kingdom	UK & Irland	0,6	0,5	0,2
Ghana	West Africa	5,5	5,7	1,7
Nigeria	West Africa	11,3	8,7	3,0

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