Erasmus School of Economics

Master's Thesis - Quantitative Finance

The effect of environmental, social and governance (ESG) ratings on credit risk in European corporates

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Abstract

In Europe, rules and regulations are requiring companies to re-assess their sustainability policies regarding investments and capital allocation. This paper is an empirical study of the relation between ESG scores and credit risk, using credit defaults swaps as a market-based proxy for credit risk. The study covers 106 large European corporations over six years (2015 to 2020) on a quarterly level. The relation between sustainability and credit risk is assessed using fixed- and random-effect panel regression models. We find a significant negative effect of ESG scores on credit default swap premia, meaning that higher ESG scores are generally accompanied with a lower credit risk. This effect is more pronounced for larger firms. Within the ESG sub-scores (Environmental, Social and Governance), Governance has the most pronounced negative effect on credit risk, followed by Environment. Interestingly, increased Social scoring has an adverse effect on credit premia, increasing credit risk. No significant differences in the effect of ESG on credit risk across countries and sectors are found. Overall, this study provides motivation for increased ESG integration in credit risk management regarding European corporates.

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Glossary

bp Basis point, or 0.01%. 13

CDS Credit default swap(s), or price of a credit default swap. 2

CSR Corporate social responsibility. 2

DE Debt-equity ratio, or leverage. 13

ESG Environment, social and governance; general sustainability score. 1

ESG-E ESG Environment sub-score. 1

ESG-G ESG Governance sub-score. 1

ESG-S ESG Social sub-score. 1

FEM Fixed-effects panel regression model. 17

MV Firm market value, expressed in USD. 13

OLS Ordinary least squares, linear regression. 20

REM Random-effects panel regression model. 17

Vol 3-month recent stock volatility. 13

Contents

1 Introduction

Sustainability is a theme that has grabbed the attention of governments, the public and investors alike over the past years. In capital markets, the term sustainability often is evaluated based on three pillars: environment, social and governance (ESG). Enhanced ESG regulations and societal pressure are forcing organizations to focus more on ESG sustainability and increase transparency in their efforts to meet sustainability goals. Research has shown a negative empirical relation between ESG and credit risk, meaning that increased ESG scores generally result in lower credit risk (Henisz and McGlinch, 2019; Devalle et al., 2017). The individuals effects of ESG sub-scores (environment (ESG-E), social (ESG-S) and governance (ESG-G)) on credit risk is, however, relatively ill-researched (EUROSIF, 2018). This research further investigates how ESG (sub-)scores affect corporate credit risk, using credit default swaps as a market-based proxy for credit risk.

ESG is a preferred construct over the more general term 'sustainability' as it gives investors a specific and data-driven approach to evaluating company sustainability. By assigning scores to the three E, S and G pillars, an overall average company ESG score is generated. The environmental pillar is evaluated based on criteria such as water use, waste management and (carbon) emissions. The social pillar evaluates a firm's human and labour rights, employee health and safety, and stakeholder relations, amongst others. The final pillar, governance, considers factors such as business ethics, corporate governance and transparency. Combined, the three pillars objectively measure how sustainable a company is, both towards the outside world (environmental and social), as well as within (governance).

Due to increased societal and consumer attention, ESG-oriented investing has experienced a considerable rise as shareholders and C-level management increasingly integrate ESG ratings in their investment process (Drei et al., 2019). Furthermore, heightened rules and regulations imposed by governing bodies have further accelerated the use of ESG's, such as the European Commission's Sustainable Finance Disclosure Regulation (EU, 2019) and the United Nations Principles for Responsible Investment (UNPRI, 2021). Due to the increase in regulations, investors such as pension funds and asset managers are actively assessing ESG performance more than ever before, and are allocating capital to higher ESG performers (Loorbach et al., 2020).

Corporate social responsibility (CSR) is a qualitative precursor to ESG, which judges firms and organisations on their efforts to positively impact society. However, CSR ultimately lacks concrete numeric criterion and scores. As a result, quantitative evaluation of CSR is rather difficult. Growth in technology and data processing have in-part enabled the uprise of ESG scores, as prior challenges such as acquiring data from reliable sources have become easier over time (Friede et al., 2015). Furthermore, modern technology allows scores to be calculated at a higher frequency, thus increasing accuracy in company evaluation. Many scholars have found positive relations between ESG and financial performance, proving how positive ESG performance can result in increased financial returns (Friede et al., 2015). However, over 85% of research concerning the influence of ESG factors on financial returns is equity linked, whilst the bond market has a share of almost 40% of sustainable investments in Europe (EUROSIF, 2018). Concluding, relatively little attention has been paid to the influence of ESG factors on credit risk.

In 2017, the UN Principles for Responsible Investment introduced the "Credit risk and ratings initiative" to bridge the ESG-credit risk gap (UNPRI, 2017). The initiative, signed by over 170 investors who collectively manage a near 40 trillion USD in assets (UNPRI, 2021), aims to enhance systematic and transparent consideration of ESG factors in the assessment of corporate creditworthiness. Although several significant relations between ESG scores and credit risk have since been found (Drei et al., 2019; Friede et al., 2015; Devalle et al., 2017), the effect of the E, S and G sub-scores has not been thoroughly been researched, and there is no academic consensus concerning which of these three pillars most significantly affects credit risk (Kim and Li, 2021; Sassen et al., 2016; Switzer and Wang, 2013).

Using credit default swaps (CDS) as a market based proxy for risk is also an ill-researched topic (UNPRI, 2017). A CDS is a contingent claim that allows the risk of a loan to be traded and is analogous to an insurance on a loan. The price of this insurance, called the CDS spread or premium, is generally considered to be an accurate market-based proxy for a firm's credit risk as it depicts how risky the insurer rates the company to be (Fabozzi et al., 2003). To the best of our knowledge, Razak et al. (2020), Hock et al. (2020) and Barth et al. (2018) are yet the only papers employing CDS spreads as a target variable in ESG research. All three papers employ panel data regressions and show that increased ESG ratings can result in lower credit risk. These papers, however, fully rely on a single regression model, being either a fixed-effects model or random-effects model and do not test their results for robustness by comparing results of two models side-to-side. Nor do these studies extensively investigate differences in ESG effect across countries, sectors and company size, which have shown to be of significant influence (Kim and Li, 2021; Barth et al., 2018).

This research therefore further builds upon existing, empirical research investigating how ESG factors influence corporate credit risk. We investigate this based on three research questions.

1. What is the effect of the general, combined ESG score on corporate credit risk?
2. What is the effect of the individual E, S and G scores on corporate credit risk?
3. How does the effect of ESG (sub-)scores differ amongst countries, sectors and company size?

This study covers 106 large European corporations over six years (2015 to 2020) on a quarterly level, and both fixed- and random-effect panel regressions are applied. Credit default swap premia are used as a target variable (y) and represent credit risk. Variables debt-equity ratio (x_1) and 3-month recent stock volatility (x_2) are used as control variables, based on Merton (1974). ESG (sub-)scores are added as final independent variable(s) (x_3) and the resulting regression coefficients are analysed to investigate the effect of ESG scoring on credit risk over various subsets.

Preceding research generally shows a negative effect of ESG scores on credit default swap premia (Hock et al., 2020; Razak et al., 2020; Barth et al., 2018). That is, higher ESG scores are generally accompanied by lower credit premia, thus lower credit risk. The limited research investigating the effect of ESG sub-scores on credit risk shows that Governance generally has the most pronounced negative effect on credit risk, and that Environment and Social efforts have little or no effect on credit risk (Switzer and Wang, 2013; Kim and Li, 2021). This research expects to find similar results.

The paper contributes to literature in the following ways: first, we further investigate the relation between ESG scores and credit risk, and utilize previously neglected CDS spreads as a proxy for credit risk (as proposed by UNPRI (2017)). Second, this paper is one of the first to further investigate the effects of the E, S and G sub-scores on credit risk. Third, this is the first paper to analyse both fixed- and random-effect panel regressions in a ESG-credit risk context. Finally, this is the first paper to study differences in the effect of ESG on credit risk across countries, sectors and company sizes. Furthermore, the empirical research has practical implications as it is part of an internship at Accenture's Risk and Compliance division in The Netherlands. We therefore focus on European corporates as research implications may be relevant for projects with European asset managers, banks or insurers.

The rest of this research contains six main text sections. Section 2 provides a brief and simplified overview of credit risk and credit default swaps for readers unfamiliar with the topic. Next, Section 3 covers existing research on the topics of ESG and CDS, and further elaborates on research hypotheses. Section 4 describes data sourcing, transformation and statistics, which will form the basis of the empirical analysis. Following, Section 5 describes the regression models and methodology used to obtain results. The results are shown and explained in Section 6. Finally, results are discussed in Section 7, followed by possibilities for further research and a general conclusion.

2 Introduction to credit risk

The following chapter will provide a simplified overview of credit risk and credit default swaps, useful to understand the implications of the research and motivation to use credit default swaps. We cover what credit risk is, what a CDS is, how a CDS is priced and what the advantages of using CDS are over other credit risk measures. Readers for whom these topics are familiar are suggested to skip to Section 3.

2.1 Credit risk

Any kind of investor that agrees to a financial transaction is faced with the odds of losing money: this is financial risk. Credit risk is a specific form of financial risk that occurs when money is loaned to a party. The risk is contained in the probability that a borrower, or debtor, is unable to repay interest or the loan to the creditor. A default is the term used when a borrower fails to repay debt or interest to the creditor, resulting in financial loss for the creditor. Note that loans can and are set out between all sorts of financial vehicles, such as banks, people, companies and even governments. This intricate credit matrix forms one of the key pillars of our financial system; the 2008 credit crisis is a testament to how essential credit constructs are in the financial system. Scholars and institutions have since increased their focus on managing credit risk and improving credit risk modelling: how do we predict a borrower's ability to repay their interest and loan?

Credit risk can be assessed in a multitude of ways, such as probability of default (i.e. what is the probability a debtor defaults), exposure at default (i.e. what is the outstanding amount if a debtor defaults), or loss given default (i.e. what percentage of the outstanding amount is lost at default), amongst others. Companies that specialise in evaluating the ability of a debtor to meet its credit obligations are called credit rating agencies. These agencies often summarize credit risk evaluation in the form of letter grades. For example, credit scores could range from CCC (maximal credit risk), to AAA (minimal credit risk). Although credit rating agencies use complex models to determine their score, credit scores differ greatly across rating agencies and scores are infrequently updated (Rablen, 2013).

2.2 Credit default swaps

Credit default swaps are financial contracts that allow creditors to minimize their credit risk. The contract is used to transfer credit risk to an "insurer". We introduce a hypothetical loan situation: Company ABC needs a 1 million EUR loan from a bank to expand business operations. The bank agrees and in return Company ABC must pay a ten percent (10%) annual interest fee for five consecutive years, after which the company must repay the 1 million EUR loan in full. As the only credit party in the deal, the bank is currently taking the full credit risk of Company ABC not meeting debt obligations. The bank therefore decides to add a new party to the agreement: the insurer. The insurance company insures the bank in case Company ABC defaults. That is, if Company ABC fails to pay the 10% annual interest or repay the loan in full, the insurer will pay the remaining outstanding amount to the bank. The bank pays the insurer a small fee in return for this service, which we set as a 2% annual fee over the outstanding 1 m EUR loan. The relations and cash flows between the Company ABC, the bank and the insurer are schematically represented in Figure 1. The enclosed relation between the bank and the insurer is called a credit default swap.

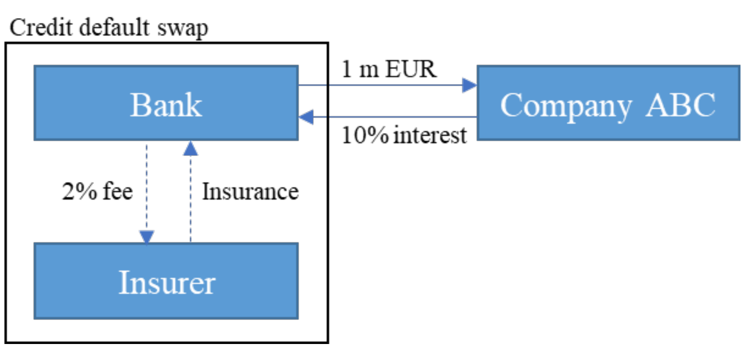


Figure 1: A schematic representation of a hypothetical credit default swap. In this example, the CDS contract between the bank and the insurance (enclosed in black) allows the bank to transfer credit risk held by the loan to Company ABC to the insurance, in return for a fee: the CDS spread.

By using a credit default swap, the bank is now able to transfer Company ABC credit risk to the insurance company for a small fee. Note that the bank is not completely free of credit risk, as there is still a chance that the insurer is also unable pay (e.g. if bankrupt).

The 2% fee paid to the insurer, expressed as a percentage of the outstanding notional loan, is the price (or spread) of the CDS. Determining this price or spread requires complex financial models as the insurer accurately wants to assess its risk. Naturally, the riskier Company ABC is evaluated to be, the higher the insurance company will price the credit default swap. The price of a CDS can therefore be used as a measure of credit risk, similar to a credit rating.

CDS spreads are becoming increasingly popular in academics as they can provide a better market-based proxy for credit risk compared to above mentioned financial metrics or credit ratings. An advantage of using CDS is that they are standardized in terms of their features, making them easily comparable across organisations (no ”translation” issues between, e.g., a B- and BBB loan). Furthermore, in contrast to bonds, CDS are not required to be corrected for different maturities, coupon effects or optionality, features which can all influence pricing (Han and Zhou, 2015; Zhang et al., 2005; Hock et al., 2020; Benkert, 2004; Ericsson et al., 2009). CDS tend to also show higher liquidity and are more responsive than corporate bond markets (Ederington et al., 2015). Finally, CDS are more frequently updated than credit ratings or other measures, making them more accurate and up-to-date (Finnerty et al., 2013).

3 Related literature and hypothesis development

This section covers existing research done on the topics of credit risk and sustainability, and the use of ESG (sub-)scores. We also cover CDS modelling, followed by the effect of ESG scores on CDS. We discuss which results have previously been obtained, which methods have been used and what are pitfalls in preceding research. We conclude the section by setting up our hypotheses.

3.1 Credit risk and ESG (sub-)scores

Over 85 percent of research concerning the influence of ESG factors in finance is equity linked (Friede et al., 2015), whilst the bond market has a market share of almost 40 percent of sustainable investments in Europe (EUROSIF, 2018). Relatively little attention has thus been paid to the influence of sustainability or ESG factors on credit risk. Up to 2017, research shows no conclusive results regarding a positive or negative relation of ESG on credit risk (Menz, 2010; Devalle et al., 2017). Since the United Nations introduced the Credit Risk and Ratings Initiative (UNPRI, 2017) aiming to *"enhance the systematic (...) consideration of ESG issues in the assessment of creditworthiness of borrowers"* there has been academic consensus on the general negative relation between sustainability and credit risk (Henisz and McGlinch, 2019; Devalle et al., 2017).

A lot of research done on the effect of sustainability on credit risk is based on a single ESG metric, despite ESG scores being a weighted average of the individual ESG-E (Environment), ESG-S (Social) and ESG-G (Governance) scores. To the best of our knowledge, only a handful of papers have analysed these ESG sub-scores in a financial context. Sassen et al. (2016) shows that increased environmental and social performance decreases total and idiosyncratic risk, but states governance does not significantly impact any form of risk. Interestingly, Switzer and Wang (2013) provides evidence that increased corporate governance does lower credit risk for public companies. Kim and Li (2021) examines the relationship between the three ESG sub-scores and corporate financial performance, and finds that governance has the most significant positive impact on financial performance. Kim and Li (2021) also observe that the effect of ESG on financial performance is more pronounced in larger firms. Concluding, research regarding the effect of ESG sub-scores on credit risk is not extensive and differs in outcomes; this topic therefore provides possibilities for further research.

Although the negative relation between general ESG scores and credit risk has proven to be conclusive, an issue in the use of ESG factors in research is the divergence and lack of commonality in ESG ratings amongst various rating agencies (Billio et al., 2021). ESG ratings can vary widely amongst providers, which can be caused by differences in sustainability constructs, as well as by methodological differences (Abhayawansa and Tyagi, 2021). This can result in the same company being ranked highly by one provider, and poorly by another (Li and Polychronopoulos, 2020). Dorfleitner et al. (2015) evaluates three large rating agencies, but finds an evident lack in convergence of ESG concepts, as well as ratings. Choosing an ESG construct that is material to one's own investment strategy therefore seems to be the best available practice (Li and Polychronopoulos, 2020; Abhayawansa and Tyagi, 2021).

3.2 Modelling credit default swaps

There are several ways in which company credit risk can be measured, e.g. probability of default, loss given default or credit ratings, amongst others. CDS spreads are becoming increasingly popular in academia as they can provide an excellent market-based proxy for credit risk (Fabozzi et al., 2003). A big advantage of using CDS is that they are standardized in terms of their features, making them easily comparable across organisations. In contrast to bonds, there is no need to correct for different maturities, coupon effects or optionality; features which can all influence pricing (Zhang et al., 2005; Hock et al., 2020; Benkert, 2004; Ericsson et al., 2009). Furthermore, CDS tend to show higher liquidity and are more responsive than corporate bond markets (Ederington et al., 2015), and have more frequent updates than credit ratings (Finnerty et al., 2013). Despite advantages over other metrics and increasing popularity, UNPRI (2017) reports the use of CDS spreads as a proxy for credit risk in ESG research to be neglected. Therefore, this research acts as a good use-case.

There are two main methods of modelling CDS, being structural models and reduced-form models. Structural models employ a Merton-based approach using market data (Black and Scholes, 1973; Merton, 1974). These models imply that the main determinants of credit risk are leverage, volatility and risk free term structure. These variables are often used as control variables in predicting corporate bonds. Note however that, compared to bond spreads, CDS spreads do not require a specification of the risk free term structure (Han and Zhou, 2015). Without a risk free term structure, the explanatory power of the control variables on CDS lies around 60 percent (Ericsson et al., 2009; Tang and Yan, 2008). The second modelling approach is a reduced-form method derived from Hull and White (2003), which postulates the dynamics of default probabilities by using market data to recover parameters needed to value credit sensitive claims. Reduced-form models have shown to be versatile in low-volatility conditions (Houweling and Vorst, 2003), but miss the link with economic fundamentals, thus compromise on explainability. Arora et al. (2005) compares the two methods side to side and concludes that in predicting CDS spreads, structural models outperform reduced-form models.

3.3 Relating ESG to CDS

Only a handful of researchers have investigated the influence of ESG factors on credit risk using CDS spreads as a proxy for credit risk. Hock et al. (2020) applies a random-effects panel regression model using a structural CDS approach with a single environmental score to measure sustainability. Hock et al. (2020) concludes that more sustainable companies generally have lower CDS spreads, and therefore have lower credit risk. The research does not, however, investigate how the effect of ESG on credit risk may differ amongst countries or sectors.

Razak et al. (2020) follows a similar random-effects approach, but builds upon Hock et al. (2020)'s research by including a country level in the model. The research finds the effect of ESG scores not to be uniform, but concludes the impact of country sustainability and corporate governance to be significant. Barth et al. (2018) published the most recent research on the matter. The research uses fixed-effect regressions and also concludes that high ESG scores are slightly related to lower CDS spreads, and thus lower credit risk. This latest research, however, does not employ a country-level variable, but splits the data in European and American countries and compares the scores, finding significant differences amongst the two. Interestingly, Barth et al. (2018) also finds a U-shaped relation across ESG quantiles, which is consistent with opposing effects of growing stakeholder influence capacity and diminishing marginal returns on ESG investments.

Concluding, all three studies show interesting results. The difference amongst countries or sectors has only been investigated between American and European companies and thus allows room for further research. Furthermore, both of the applied regression models (fixed- and random-effects) have not been compared side-to-side to strength-test results.

3.4 Hypothesis development

Research has shown that ESG factors are generally negatively correlated with company credit risk (Henisz and McGlinch, 2019; Devalle et al., 2017). Credit default swap spreads have also proven to be an excellent proxy for credit risk (Fabozzi et al., 2003). Therefore, our first hypothesis is:

Hypothesis 1: There is a negative relation between ESG scores and credit default swap premia.

Next, Kim and Li (2021); Sassen et al. (2016) and Switzer and Wang (2013) show that analysing ESG sub-scores can further pinpoint which factors significantly affect credit risk. It is likely that the effect of corporate governance is the most pronounced. Our second hypothesis therefore is:

Hypothesis 2: Within ESG sub-scores, the effect of Governance has the most prominent, negative effect on credit risk, with the Environmental and Social sub-scores being of lesser or insignificant influence.

Finally, Barth et al. (2018) has found the effect of ESG scores on credit risk to differ amongst regions, specifically Europe and America. Also, Kim and Li (2021) has shown to find a size effect, where the effect of ESG on financial performance is more pronounced in larger companies. Our third and final hypothesis therefore is:

Hypothesis 3: The effect of ESG on credit risk differs significantly across countries and sectors. Furthermore, we expect a stronger negative effect of ESG (sub-)scores on credit risk for larger companies.

4 Data

The following section covers the data used in the research in three subsections. First, we describe how all data is collected. Second, we cover data processing: the handling of outliers, and the joining of data sets. Third, we provide a brief overview of data statistics.

4.1 Data sourcing

Section 3.2 discusses the use of structural and reduced-form methods to model CDS and shows that a structural, Merton-based approach outperforms reduced-form models (Arora et al., 2005). Furthermore, structural models have increased economic interpretability due to the use of firm-level variables. Therefore, this research uses a structural approach when modelling CDS. The data necessary for this research is split in three categories: CDS data, firm-level data and ESG data.

All data is sampled on a quarterly basis (Q1-Q4) over a six year time frame ranging from 2015 up to and including 2020. We choose to not sample prior to 2015 as ESG data has experienced a significant increase in quality since 2015 (UN, 2015). Furthermore, post 2020 data is purposefully excluded as firm-level data is often not yet fully available.

Sustainability data is derived from Arabesque, a data-analytics company that analyses sustainability performance metrics to create firm ESG ratings on a 0-100 scale (100 being a perfect score). Arabesque outperforms competitor scoring agencies in terms of accuracy by using Machine Learning techniques and sourcing data from 1700 sources, as well as scoring companies more frequently (quarterly opposed to annually) (Arabesque, 2022). Due to a joint-venture between Accenture and Arabesque, the full data set is freely available for the research. The data set covers over 2000 large European companies and their respective ESG scores. Each observation contains one total average ESG score and three sub-scores: Environment, Social, and Governance. The general ESG score is a near-equally weighted average of the sub-scores. A further breakdown of which criteria are used to determine sub-scores is found in Appendix A.1.

CDS data is derived from Thomson's Refinitiv Eikon engine, accessed through the Erasmus University Rotterdam Data Science Centre. The database is used to extract as many five year CDS spreads for all firms covered in the Arabesque data set. We choose to focus on five year CDS contracts as they are the most liquid and constitute the majority of the CDS market (Razak et al., 2020). Data sourcing has shown that although CDS are a common credit derivative, CDS spreads are not always publicly available: we are able to derive CDS data for roughly 120 companies out of the approximately 2000 companies in the ESG data base. The extracted CDS spreads are expressed in basis points (bp).

Firm-level data is also derived from the Thomson Refinitiv Eikon engine, similar to CDS data. It is used to extract firm-level variables based on the structural Merton-based modeling approach of CDS. The extracted company variables are total market value (MV) in US Dollars, debt-equity ratio (DE) in percentages, and 3-month recent stock volatility (Vol). Company leverage is only available on an annual level, therefore Q1-Q4 leverage observations over a single year are identical. We assume leverage to remain relatively constant over an annual time frame, therefore this influence is minimal.

4.2 Data handling

The three data sets are subsequently merged based on International Securities Identification Number codes, a unique 12-digit alphanumeric code that identifies a company. Data handling is done using Python. Companies for which no CDS data is available or all CDS observations are constant over time are omitted as these observations have no variance. Companies for which one or more of the firm-level variables are unavailable over the full time frame are also omitted. Furthermore, to ensure our results are not driven by extreme values or errors in the data, we perform a brief outlier analysis. Zhang et al. (2005) and Barth et al. (2018) propose to omit CDS values over 4000 bp, and Giglio (2016) shows CDS spreads in excess of 1000 bp are often caused by near bankruptcy. We therefore omit all firms containing CDS values above 1000 bp, roughly 2% of all data. We choose to omit leverage ratio values above 1000 and below -500 (roughly 1% of all data), based on Martikainen et al. (1995). The remaining variables do not contain outliers that need to be omitted. All regression variables are denoted on a relative scale and therefore do not need to be normalized.

4.3 Data statistics

The final panel data set covers 2343 quarterly observations distributed over 106 large European corporates, equating to roughly 22 observations per company on average. Firms that contain data over the full time frame (Q1 2015, ..., Q4 2020) cover 24 observations (4 quarters over 6 years). All firms cover a continuous period without data breaks, thus missing observations are only missing at the beginning or end of the time frame. A few examples of companies included in the set are Akzo Nobel, Volkswagen, NXP Semiconductors and Adidas, amongst others. A full overview of all company names can be found in Appendix A.2.

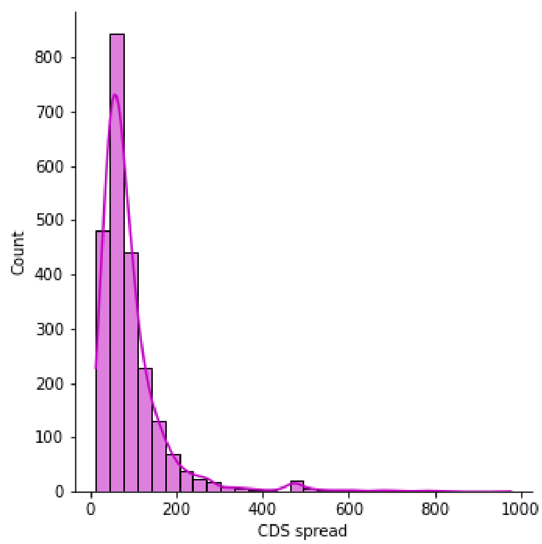
The quarterly observations are distributed over 16 sectors and 16 European countries. We find that more than half of all observations fall within three countries, being the United Kingdom, Germany and France, which is generally consistent with the distribution of large corporates in Europe. For some countries, such as Russia, Belgium and Greece, the data set only contains data of one company (or 22 observations). The observations are more evenly distributed over the sectors, with the three most represented sectors being Process Industries, Utilities and Producer Manufacturing. Furthermore, that data is balanced regarding year and quarter. A full overview of all countries, sectors and years, including respective sampling distributions, is shown in Appendix A.3.

Table 1: Summary statistics of all variables used in the empirical regression analysis. Standard deviation is abbreviated with SD, and Q represents Quantile.

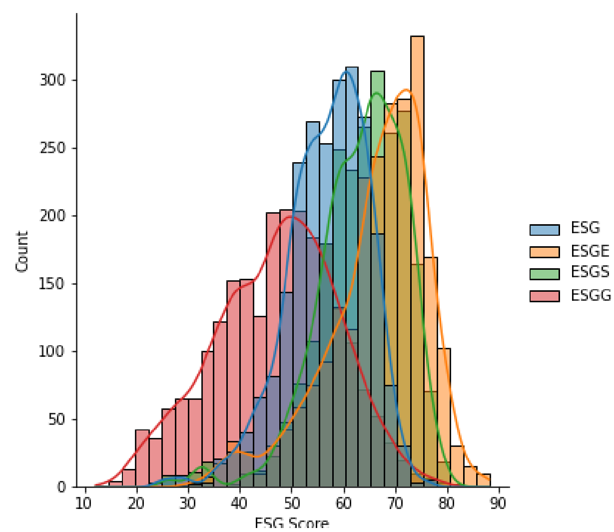
Variable	Count	Mean	Median	SD	Skewness	Kurtosis	Q (25%)	Q (75%)
CDS	2343	95.4	70.5	91.1	4.0	21.2	49.9	108.4
DE	2343	117.7	80.5	130.4	2.5	9.9	48.2	143.7
Vol	2343	0.3	0.2	0.2	2.8	11.2	0.2	0.3
ESG	2343	56.9	57.8	7.9	-0.7	1.0	52.1	62.7
ESG-E	2343	66.4	68.3	9.9	-1.0	1.0	61.5	73.6
ESG-S	2343	63.5	64.7	8.5	-1.1	2.3	58.6	69.8
ESG-G	2343	47.1	48.0	11.9	-0.2	-0.3	38.9	55.4

An overview of basic summary statistics of all variables is shown in Table 1. The average CDS spread is 95.4 basispoints, or 0.954%, which is consistent with other research (Hock et al., 2020; Razak et al., 2020). We observe that CDS, DE and Vol are right-skewed, have a high kurtosis and a standard deviation almost equal to their respective mean. On the other hand, all ESG scores are left-skewed and have a relatively low kurtosis, indicating a light-tailed distribution.

We further explore the distributions of CDS spreads and ESG (sub-)scores using Figures 2a and 2b, which show a distribution plot the respective variables. The right-skewness of the CDS spread and left-skewness of the ESG scores are clearly visual. The average total ESG score is 56.9. ESG sub-scores ESG-E and ESG-S average at 66.4 and 63.5 respectively, above the general ESG average. These higher scores may be attributed to increased focus on these pillars due to social and regulatory pressure. The third pillar, ESG-G, scores the lowest of the three with an average score of 47.1.



(a) A distribution plot of all CDS spreads, expressed in basis points (bp). The average spread is 95.4 bp (0.954%).



(b) A combined distribution plot of the general ESG score and the three ESG sub-scores: environment (ESGE), social (ESGS) and governance (ESGG)

Figure 2: Distribution plots for two key research variables: CDS spreads and ESG (sub-)scores.

A basic correlation matrix is shown in Figure 3 and helps to predict initial relations between variables. Overall, few strong correlations (that is, over 0.6) are found, except amongst the ESG (sub-)scores. Volatility and debt-equity, used as control variables, are moderately correlated to our CDS target variable, 0.38 and 0.14 respectively. This indicates that volatility perhaps is a better indication of credit default swap premia than leverage. The general ESG score has a -0.2 correlation to CDS, indicating a negative (univariate) relation, as expected. The ESG (sub-)scores do display higher levels of correlation amongst each other, specifically ESG and ESG-G (0.83).

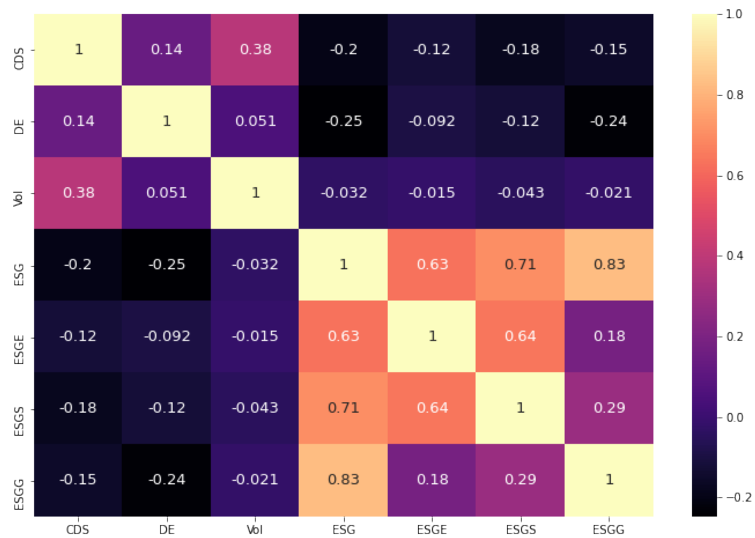


Figure 3: A heatmap correlation matrix of all variables, used to identify initial relations amongst variables.

The correlation matrix (Figure 3) shows basic, univariate correlations between two variables. This univariate effect does not, however, directly scale or sum to multivariate analysis, when the effect of multiple independent variables on a dependent variable are analysed. Nonetheless, keeping this in mind, the correlation matrix serves as a good indication of basic relations between the variables. The multivariate relations are further investigated using regression analysis in the following sections.

5 Methodology

This section describes the methodology used to answer our research questions. We cover the (in)dependent variables used and introduce two panel regression models. Next, we explain how the data is split and which regressions are applied.

5.1 Variables

An overview of the variables used is shown in Table 2. As the research goal is to highlight the effect of ESG on credit risk, we choose to only use leverage and 3-month recent stock volatility as control variables, based on Merton (1974). All variables are available at company, quarterly level. Furthermore, country, sector and market value are specified for all companies.

Table 2: Overview of all company variables used in regressions analysis. The three ESG-E, ESG-S and ESG-G scores are always used separately from the general ESG score.

Abbreviation	**Description**
	Dependent variable
CDS	5-year credit default swap spread, or price, in basis points
	Independent variables
DE	Debt-equity ratio, or leverage
Vol	3-month recent stock volatility
ESG	General sustainability score, rated 0-100. Average of E, S and G scores
ESG-E	Environment sustainability score, rated 0-100
ESG-S	Social sustainability score, rated 0-100
ESG-G	Governance sustainability score, rated 0-100

5.2 Panel regression

Our data set consists of observations of entities collected over time, also known as panel- or longitudinal data: it is a combination of cross-sectional and time-series data. Two widely-used panel regressions are fixed-effect models (FEM) and random-effect models (REM). Both models account for grouped structures in data, such as quarterly observations of companies, and have previously independently been used in ESG-CDS research (Barth et al., 2018; Hock et al., 2020; Razak et al., 2020). How to best choose between these models is a topic of statistical debate, as both models entail different assumptions (Nikolakopoulou et al., 2014; Naghi, 2019). The basic FEM assumption is that all groups, or companies, share a "fixed" common effect, whereas REM allows for the effect to vary over companies. FEM thus investigates variance of observations within a company, whereas REM investigates the variance across companies or groups.

In companies with few observations or low sample-to-sample variability, FEM estimates may diverge considerably from the true effect. REM generally results in more stable estimators for sets with low sample-to-sample variability (Clark and Linzer, 2012). A drawback of REM, however, is the problem of bias that partial pooling can introduce in estimates. To avoid this, REM assumes no correlation between the independent variable x_{it} and unit effects α_i: $cov(\alpha_i, x_{it}) = 0$. This partial pooling bias does not occur in FEM, and FEM only assumes $cov(\alpha_i, x_{it}) \neq 0$. Nikolakopoulou et al. (2014) and Clark and Linzer (2012) analyse the implications of these differences by means of a Monte Carlo simulation. The research concludes that if variation within units is high, FEM and REM produce similar results. If variation primarily occurs across units, model choice is dependent on the number of groups and number of observations within the groups. For data sets containing many groups (> 10), and many observations per unit (> 5), FEM is generally preferred, unless the correlation between the regressor and unit effects is close to zero.

Our data set covers 106 companies (> 10 groups) with an average of 22 observations per firm (> 5). Based on Nikolakopoulou et al. (2014) and Clark and Linzer (2012), we expect to prefer FEM over REM. We also expect the correlative effect between the unit effects and explanatory variables to be larger than zero, as we expect firms to share a common, European effect. This hypothesis also favors FEM (Nikolakopoulou et al., 2014; Clark and Linzer, 2012). Furthermore, the summary statistics (Table 1) and distribution plots (Figure 2) show high deviation across variables. These overviews do not, however, investigate sample-to-sample variability within or across companies. Therefore, no concrete model preferences can be made based on Clark and Linzer (2012), which prefers REM in low sample-to-sample variability sets.

The difference in FEM and REM model assumptions can also be tested using a Hausman test, which detects a violation of $cov(\alpha_i, x_{it}) = 0$. In-practice, however, the true correlation between covariates and unit effects is never exactly zero, therefore making the Hausman test unreliable (Clark and Linzer, 2012; Nikolakopoulou et al., 2014). Several other researches have further confirmed that the Hausman test is not a reliable tool in model choice due to the strict exogeneity assumption and the power of the test being low for typical sample sizes (Gardiner et al., 2009). A solution to circumvent choosing between the models is to create a combined score by weighing both scores based on model variance and sample size (Borenstein et al., 2010; Borenstein and Hedges, 2007). Schmidt et al. (2009), however, finds that applying such procedures results in confidence intervals that are 52% lower than their actual width, therefore deeming a combined score useless.

Concluding, choosing between REM and FEM is a complicated matter. REM is generally preferred and leads to more accurate results. This, however, is only true under the condition that $cov(\alpha_i, x_{i,t}) = 0$ holds, which is often implausible in empirical research (Clark and Linzer, 2012). Furthermore, a brief data analysis indicates FEM perhaps better suits our data. Schmidt et al. (2009) concludes by stating that the most effective solution is to use both models, analyse if coefficients and p-values are similar, and evaluate fit based on R^2. We therefore choose to use both FEM and REM models as there is no conclusive answer whether to use one model or the other (Nikolakopoulou et al., 2014), and comparing the results and fit of both models acts as a robustness check (Schmidt et al., 2009).

The next subsections explain both FEM and REM panel regression models in more statistical detail. All following theory, equations and assumptions are cited or derived from Naghi (2019):

Suppose we have a panel data set y_{it} and $x_{it} = (x_{1it}, x_{2it}, ..., x_{Kit})'$ with $i = 1, ..., N$ and $t = 1, ..., T$. The goal is to explain y in terms of the x's, using the general linear specification shown in Equation 1:

$$y_{it} = \alpha_{it} + x'_{it}\beta_{it} + \varepsilon_{it} \tag{1}$$

Here, y_{it} is the dependent or target variable and x_{it} the vector of independent variables. Coefficients α_{it} and β_{it} are the unknown parameters of interest. Furthermore, ε_{it} is the non-observable random error term. All following regressions and equations follow an identical notation as shown in the general linear specification (Equation 1). Potential regression alterations are explained as needed.

5.2.1 Fixed-effect models

Fixed-effect models are a type of model which analyse variation of variables within groups, or companies. The group mean parameters are fixed and non-random, hence the name. All following theory, equations and assumptions are (still) cited or derived from Naghi (2019). First, we restrict Equations 1's $\alpha_{it} = \alpha_i$ for all t and $\beta_{it} = \beta$ for all i and t. By fixing α_i, the intercept can incorporate heterogeneity amongst classes and the intercept is treated as an incidental parameter. The resulting model under these restrictions is shown in Equation 2:

$$y_{it} = \alpha_i + x'_{it}\beta + \varepsilon_{it} \tag{2}$$

Equation 2 shows how FEM creates a time-invariant intercept α_i for groups. This allows for endogeneity in α_i, meaning α_i is allowed to correlate with the independent variables x_{it}: $cov(\alpha_i, x_{it}) \neq 0$. Endogeneity can cause coefficients to become biased as some of the error term variance is explained by α_i. The next step in setting up the fixed-effects model is averaging Equation 2 over time t for each classification i, shown in Equation 3:

$$\bar{y_i} = \alpha_i + \bar{x_i}'\beta + \bar{\varepsilon_i} \tag{3}$$

Here, $\bar{y_i} = \frac{1}{T}\sum_{t=1}^{T} y_{it}$, $\bar{x_i} = \frac{1}{T}\sum_{t=1}^{T} x_{it}$ and $\bar{\varepsilon_i} = \frac{1}{T}\sum_{t=1}^{T} \varepsilon_{it}$. The time-average of α_i has no time component and is therefore equal to itself: $\frac{1}{T}\sum_{t=1}^{T} \alpha_i = \bar{\alpha_i} = \alpha_i$. Subsequently, we subtract Equation 3 from Equation 2 to yield Equation 4:

$$(y_{it} - \bar{y_i}) = (x_{it} - \bar{x_i})'\,\beta + (\varepsilon_i - \bar{\varepsilon_i}) \tag{4}$$

By applying ordinary least squares (OLS) on Equation 4 we obtain the "within" fixed estimator. By means of this transformation we get rid of the individual effects (α_i) and only the idiosyncratic error remains. Therefore, this estimator only explores variation of variables *within* companies over time, and does not account for cross-sectional variation *between* companies. For this same reason, the within-estimator cannot handle time-independent (dummy) variables, such as country or sector.

5.2.2 Random-effect models

All following theory, equations and assumptions are (still) cited or derived from Naghi (2019). Random-effect models also restrict $\alpha_{it} = \alpha_i$ and $\beta_{it} = \beta$, similar to FEM (see Equation 2). REM differ from FEM in that the individual unobserved heterogeneity α_i is assumed to be uncorrelated with the independent variables x_{it}: $cov(\alpha_i, x_{it}) = 0$. By means of this assumption, α_i can now be treated as a part of the error term and we re-write Equation 2 as shown in Equation 5.

$$\begin{aligned} y_{it} &= \alpha_i + x'_{it}\beta + \varepsilon_{it} \\ &= \alpha + x'_{it}\beta + (\alpha_i - \alpha + \varepsilon_{it}) \end{aligned} \tag{5}$$

Here, the new term α is the global intercept. Similar to FEM, we take the time-average over Equation 5:

$$\begin{aligned} \frac{1}{T}\sum_{t=1}^{T} y_{it} = \bar{y_i} &= \frac{1}{T}\sum_{t=1}^{T} (\alpha + x'_{it}\beta + \alpha_i - \alpha + \varepsilon_{it}) \\ &= \alpha + \bar{x_i}'\beta + (\alpha_i - \alpha + \bar{\varepsilon_i}) \\ &= \alpha + \bar{x_i}'\beta + \bar{u_i} \end{aligned} \tag{6}$$

The term $\bar{u_i}$ is a new, combined error term that incorporates α_i, α and $\bar{\varepsilon_{it}}$. Furthermore, we assume $\alpha_i \sim iid(\alpha, \sigma_\alpha^2)$, $\varepsilon_{it} \sim iid(0, \sigma_\varepsilon^2)$. By appling OLS over Equation 6 we obtain the "between" random estimator. This model only uses cross-sectional variation *between* companies for parameter estimation, compared to the "within" FEM that uses variation *within* companies. This section concludes all equations and theory derived from Naghi (2019).

5.3 Performing the regressions

Having set-up the data, variables and regression models, we now perform the regressions using our data set. We choose to use both FEM and REM models as there is no conclusive answer whether to use one model or the other (Nikolakopoulou et al., 2014) and comparing the results of both models acts as a robustness check (Schmidt et al., 2009). In the following section, "regressions" refers to both the FEM and REM regressions.

5.3.1 Full data set

First, we investigate the general effect of ESG scores on credit risk for the entire data set. We use CDS as independent variable ($y_{it} = CDS_{it}$), and use the control variables (Volatility and Debt-Equity ratio) and the general ESG score as independent variables $x_{it} = (Vol_{it}, DE_{it}, ESG_{it})'$. The resulting equation, based on the general linear specification (Equation 1), is shown in Equation 7.

$$CDS_{it} = \alpha_{it} + (Vol_{it}, DE_{it}, ESG_{it})'\beta_{it} + \varepsilon_{it} \tag{7}$$

Here, subscripts i and t represent company (i = 1, ..., 106) and time (t = Q1 2015, ..., Q4 2020). Subsequently, we apply both panel regression models, FEM and REM, as shown in Sections 5.2.1 and 5.2.2, respectively. The results are used to test Hypothesis 1, which expects a significant, negative ESG regression coefficient for both the FEM and REM regression models.

Next, we investigate the effect of ESG sub-scores on credit risk for the entire data set. We perform a regression similar to Equation 7 using CDS as dependent variable, and DE and Vol as independent variables. However, we now replace the general ESG score with the three ESG sub-scores. That is, $x_{it} = (Vol_{it}, DE_{it}, ESG - E_{it}, ESG - S_{it}, ESG - G_{it})'$. The resulting specification is shown in Equation 8.

$$CDS_{it} = \alpha_{it} + (Vol_{it}, DE_{it}, ESG - E_{it}, ESG - S_{it}, ESG - G_{it})'\beta_{it} + \varepsilon_{it} \quad (8)$$

Again, subscripts i and t represent company (i = 1, ..., 106) and time (t = Q1 2015, ..., Q4 2020) and we apply both panel regression models. The results are used to answer Hypothesis 2, which expects a significant, negative ESG-G score and lesser or insigificant ESG-E and ESG-S scores. The general ESG score and ESG sub-scores are always applied in separate equations to prevent (multi)collinearity issues and maximise the explanatory power of the sub-scores.

For both regression specifications, general ESG (Equation 7) and ESG sub-scores (Equation 8), we also note the resulting R^2, as proposed by Schmidt et al. (2009). The R^2 is a measure that calculates which proportion of the variance in our dependent variable is explained by our independent variables. In short, the R^2 is a 0 to 1 scale measure of model fit (1 being a perfect fit). The results are partly used to evaluate which of the two regression models, FEM of REM, are a better fit for our data.

5.3.2 Split over country, sector and size

After performing both the general ESG and ESG sub-score regressions over the full data set, we investigate the same effect across three data splits. The three investigated classifications are:

- **Country:** differences across countries in the set
- **Sector:** differences across sectors in the set
- **Size:** differences across three company sizes based on market value: small (0-10 billion USD), medium (10-40 billion USD) and large (40+ billion USD)

For each subset within the split, both the general ESG regression (Equation 7) and sub-score ESG regression (Equation 8) are performed, using both the FEM and REM panel regression models. Therefore, per (subset) split, we perform four separate regressions. We do not note the R^2 of these regressions as the R^2 is only used in determining model fit over the entire data set. Hypothesis 3 states that we generally expect to find negative ESG coefficients, and negative ESG-G and insignificant ESG-E and ESG-S coefficients, with some variation in coefficients across the splits. Furthermore, we expect a stronger negative effect of ESG (sub-)scores on credit risk for larger companies, i.e. a size effect.

We have previously acknowledged that our data set is not perfectly balanced over countries and sectors (see Appendix A.3). Therefore, by splitting the data into subsets, we expose subsets containing relatively few firms or observations. Analysing an effect based on a single firm is unreliable as a single firm does not represent all sectors, sizes, or other factors present. In an attempt to create reliable results, we therefore choose to only analyse subsets containing 150 or more observations (or roughly 6-7 companies).

6 Results

This section discusses results obtained following the methodology described in Section 5. We first discuss the effects of general ESG score and ESG sub-scores on the full data set, after which we present the differences across countries, sectors and sizes.

6.1 General ESG

To test the effect of the general ESG score on credit risk we regress Volatility, Debt-Equity ratio and ESG scores on credit default swaps over the full data set (see Equation 7). Volatility and Debt-Equity are used as control variables. The results are summarized in Table 3. The fixed-effect model does not return an intercept, as explained in Section 5.2.1. Based on Hypothesis 1, we expect a significant, negative ESG coefficient for both models.

Table 3: Regression results investigating the effect of the general ESG score on credit risk over the full data set. Debt-equity ratio (DE) and Volatility (Vol) are used as control variables. Standard errors are noted in parentheses. P-values are noted as: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Model	**Intercept**	**DE**	**Vol**	**ESG**	R^2
Fixed-effects	-	0.01 (0.01)***	137.8 (6.49)***	-0.3 (0.27)	0.31
Random-effects	85.6 (16.56)***	0.1 (0.01)***	138.6 (6.51)***	-0.6 (0.26)**	0.17

From Table 3, we observe that both control variables Volatility and Debt-Equity ratio are significant for both models (1%). Most explanatory power is derived from Volatility, indicating that 3-month recent stock volatility is a good predictor of credit default swap premia, as predicted based on the correlation matrix (Figure 3). Furthermore, the control variable coefficients are similar over the two models. From the ESG coefficients we observe that the fixed-effect model results in an insignificant -0.3 ESG coefficient, and the random-effects model results in a (5%) significant -0.6 coefficient. The ESG coefficients for both models are negative, as expected, indicating that firms with higher ESG scores generally have lower credit default swap premia. The values of the coefficients are interpreted such that per unit ESG score increase, firm swap premia respectively decrease by 0.3 to 0.6 bp, given all else remains equal. This means that for two firms of which one's ESG score is 10 points higher, their CDS premium generally is 0.3 to 0.6% lower, ceteris paribus. However, as both models result in different coefficients and p-values, it is hard to conclusively interpret this effect.

Comparing the overall R^2 values of FEM and REM, we observe that the fixed-effect model has a higher fit (0.31) compared to the random-effect model (0.17), indicating that FEM might be a better fit for our data, as expected. Both R^2 values are low and do not match the indicated 0.5 to 0.6 R^2 using these control variables, shown by Ericsson et al. (2009). A low R^2, however, does not change the interpretation of the coefficients and p-values, but rather indicates that the scatter around our regression line is high.

6.2 ESG sub-scores

Section 6.1 investigates the effect of the general ESG score on credit risk. This section investigates the effect of the three ESG sub-scores, as shown in Equation 8, using the same full data set and control variables. The results are summarized in Table 4. A significant, negative ESG-G score and lesser or insigificant ESG-E and ESG-S scores are expected, based on Hypothesis 2.

Table 4: Regression results investigating the effect of ESG sub-scores on credit risk over the full data set. Debt-equity ratio (DE) and Volatility (Vol) are used as control variables. Standard errors are noted in parentheses. P-values are noted as: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Model	Intercept	DE	Vol	ESG-E	ESG-S	ESG-G	R^2
Fixed-effects	-	0.1 (0.01)***	138.7 (6.49)***	0 (0.24)	0.5 (0.27)*	-0.3 (0.16)*	0.53
Random-effects	55.1 (18.23)***	0.1 (0.01)***	139.4 (6.52)***	-0.1 (0.24)	0.3 (0.26)	-0.3 (0.16)**	0.15

Table 4 shows that the control variable coefficients are near identical between the FEM and REM models, and are all significant at a 1% confidence level. The control coefficients are also similar to the general ESG regression control coefficients in Table 3.

We observe that the ESG sub-scores, however, display varying effects on credit risk. The effect of the Environmental sub-scores are 0 and -0.1 for the FEM and REM models, respectively. Both coefficients do not differ significantly from zero and have large standard deviations, indicating that environmental efforts do not significantly affect corporate credit risk, as expected. The effect of Governance is more pronounced: the coefficients of both the FEM and REM models result in identical, significant ESG-G coefficients of -0.3. This indicates that enhanced governance efforts significantly decrease credit premia, as predicted. The Social score, however, displays unexpected regression results: it is the only sub-score to result in positive coefficients, whereas an insignificant (negative) effect was predicted. This implies that increased Social sustainability efforts increase credit default swap premia, and thus have an adverse effect on credit risk. However, as the REM ESG-S coefficient is insignificant, it is again difficult to draw strict conclusions and generalize the impact of Social efforts on credit risk.

By employing ESG sub-scores instead of the general ESG score, the FEM model overall R^2 has increased from 0.31 to 0.52, thus increasing model fit to expected values (Ericsson et al., 2009). The REM R^2, on the other hand, has decreased from 0.17 to 0.15. This decreased fit could indicate that the random-effect models may not be an appropriate fit for our data set, which is further discussed in Section 7.

6.3 Country effects

We now analyse the country-specific effects of ESG ratings on credit risk. Both previous regressions, using the general ESG score and ESG sub-scores, are performed. The data is now, however, split in 16 country subsets, with each subset containing all observations of one country. In an attempt to create balanced subsets, subsets containing less than 150 observations are omitted; 5 countries remain. The results are summarized in Table 5. Control variable coefficients and R^2 are also omitted from the table, as these are more appropriately analysed using the full data set.

Table 5 shows varying ESG effects over the five most-represented countries in our set. We generally expect negative ESG coefficients, and negative ESG-G and insiginificant ESG-E and ESG-S coefficients for both regressions respectively, with some variation across countries. The United Kingdom covers almost 28% of the entire data set (647 out of 2343 observations), therefore it is no surprise that these country-specific effects are similar to the average, full data set results. Additionally, the United Kingdom's ESG and ESG-G coefficients are more significant than the average model. Spain displays extremely significant, negative coefficients for both the FEM and REM models. The country boasts a (1% significant) -2.7 ESG coefficient and -2.5 ESG-G coefficient. Interestingly, most Spanish companies in the data set are partly government-owned, such as Iberdrola (utilities) and Telefonica (communications).

Table 5: Regression results investigating the effect of ESG (sub-)scores on credit risk across countries, for fixed and random effect models. Only countries containing 150 or more observations (n) are shown. For both FEM and REM models, the table shows ESG coefficients of two separate regressions: one using the general ESG score (Equation 7), and the other using ESG sub-scores (Equation 8). All regressions use debt-equity ratio (DE) and volatility (Vol) as control variables, which are not displayed. Standard errors are noted in parentheses. P-values are noted as: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Fixed-effects regression					
Country	**ESG**	**ESG-E**	**ESG-S**	**ESG-G**	**n**
All	-0.3 (0.27)	0 (0.24)	0.5 (0.27)*	-0.3 (0.16)*	2343
United Kingdom	-1.3 (0.52)**	0.2 (0.43)	0.2 (0.53)	-0.9 (0.3)***	647
Germany	-0.6 (0.38)	0.5 (0.34)	-0.8 (0.34)**	-0.1 (0.22)	424
France	3.1 (1.07)***	3 (0.99)***	0.7 (1.24)	1.1 (0.53)**	285
Sweden	-0.2 (0.44)	0 (0.4)	-0.9 (0.36)**	0.2 (0.21)	168
Spain	-2.7 (0.89)***	-1 (0.69)	0.8 (0.72)	-2.4 (0.61)***	150

Random-effects regression					
Country	**ESG**	**ESG-E**	**ESG-S**	**ESG-G**	**n**
All	-0.6 (0.26)**	-0.1 (0.24)	0.3 (0.26)	-0.3 (0.16)**	2343
United Kingdom	-1.3 (0.5)**	-0.2 (0.4)	-0.3 (0.51)	-0.6 (0.28)**	647
Germany	-0.6 (0.37)	0.5 (0.33)	-0.8 (0.33)**	-0.1 (0.22)	424
France	0.9 (1.05)	-0.3 (0.95)	-0.1 (1.23)	0.8 (0.57)	285
Sweden	0.1 (0.4)	0.3 (0.37)	-0.8 (0.35)**	0.2 (0.21)	168
Spain	-2.7 (0.69)***	-1 (0.65)	0.7 (0.7)	-2.5 (0.57)***	150

France shows divergent behaviour, being the only country to result in a positive ESG-credit risk relation (for both models). France's ESG sub-scores are also all (significantly) positive in the FEM model. The French REM coefficients, however, are not significant, which could be attributed to bad model fit. France's subset contains 13 countries from 10 sectors and is thus is reasonably balanced. Furthermore, Germany and Sweden show insignificant or mixed results, except for significantly negative Social scores. This contradicts the positive, adverse effect ESG-S had on credit risk over the full data set. Overall, most countries behave as expected, except for France, and Germany and Sweden with negative Social coefficients. The coefficients between the FEM and REM models remain fairly similar, however, a larger amount of FEM coefficients are significant.

6.4 Sector effects

We now analyse the sector-specific effects of ESG on credit risk, similar to the country-specific regressions in Section 6.3. Again, we use the general ESG score and ESG sub-scores in separate regressions (see Equations 7 and 8, respectively). Out of the total 16 sectors in our set, 7 sectors contain 150 or more observations. Subsets containing less than 150 observations are omitted to create balanced subsets. The regression results are summarized in Table 6.

We, again, expect negative ESG coefficients for the general ESG regression, and negative ESG-G and insiginificant ESG-E and ESG-S coefficients for the ESG sub-score regression. Table 6 shows few coefficients are significant. Most coefficients that are significant, however, are negative ESG or ESG-G effects, as expected. The Consumer Non-Durables sector, which mainly markets food and beverages, stands out with a 1% signficiant -1.2 ESG coefficient and 5% significant -1.8 ESG-G effect. The ESG score in the Process Industries sector, which includes Chemical companies such as Akzo Nobel and BASF, is also significantly negatively related to credit risk.

As predicted, the ESG-E and ESG-S coefficients are mostly insignificant. Some sectors such as Utilities and Commercial Services have a positive, significant ESG-S score, which matches previous positive ESG-S coefficients. Other sectors, such as Utilities and Producer Manufacturing, seem to show a generally positive ESG relation to credit risk. These coefficients are not significant, however. No further interesting, aberrant or significant coefficients in the sector-specific results are observed.

6.5 Size effects

Finally, we analyse size-specific effects. The data set is split in three sizes based on company market value in US Dollars: size 1 ($0-10 bn), size 2 ($10-40 bn) and size 3 ($40+ bn). The size subsets all contain over 150 observations and are reasonably equally weighted. Identical to the country and sector split, we use the general ESG score and ESG sub-scores in separate regressions. The regression results are summarized in Table 7. We expect to observe a size effect, that is, a stronger negative effect of ESG (sub-)scores on credit risk for larger firms.

Table 6: Regression results investigating the effect of ESG (sub-)scores on credit risk across sectors, for fixed and random effect models. Only sectors containing 150 or more observations (n) are shown. For both FEM and REM models, the table shows ESG coefficients of two separate regressions: one using the general ESG score (Equation 7), and the other using ESG sub-scores (Equation 8). All regressions use debt-equity ratio (DE) and volatility (Vol) as control variables, which are not dissplayed. Standard errors are noted in parentheses. P-values are noted as: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Fixed-effects regression					
Sector	**ESG**	**ESG-E**	**ESG-S**	**ESG-G**	**n**
All	-0.3 (0.27)	0 (0.24)	0.5 (0.27)*	-0.3 (0.16)*	2343
Process Industries	-0.7 (0.39)*	0.7 (0.44)	0.6 (0.32)*	-0.7 (0.2)***	255
Utilities	0.3 (0.33)	-0.2 (0.34)	1.3 (0.36)***	-0.5 (0.24)**	250
Producer Manufacturing	0 (0.34)	0.7 (0.28)**	-0.3 (0.34)	0 (0.16)	215
Consumer Services	-1.1 (0.69)	-0.2 (0.45)	-1.3 (0.75)*	-0.3 (0.35)	200
Consumer Non-Durables	-1.3 (0.28)***	-0.2 (0.31)	0.3 (0.27)	-0.8 (0.15)***	192
Non-Energy Minerals	-0.2 (1.61)	-1.1 (1.36)	2.4 (1.81)	0 (0.95)	191
Commercial Services	0.8 (0.39)**	0.4 (0.32)	0.9 (0.35)**	0.1 (0.23)	166
Random-effects regression					
Sector	**ESG**	**ESG-E**	**ESG-S**	**ESG-G**	**n**
All	-0.6 (0.26)**	-0.1 (0.24)	0.3 (0.26)	-0.3 (0.16)**	2343
Process Industries	-0.7 (0.39)*	0.8 (0.43)*	0.5 (0.32)	-0.7 (0.2)***	255
Utilities	0.2 (0.3)	-0.2 (0.34)	1.1 (0.36)***	-0.4 (0.22)*	250
Producer Manufacturing	0.1 (0.33)	0.2 (0.25)	0.3 (0.32)	0 (0.16)	215
Consumer Services	-1.2 (0.68)*	-0.2 (0.44)	-1.4 (0.74)*	-0.3 (0.34)	200
Consumer Non-Durables	-1.2 (0.27)***	-0.3 (0.3)	0.3 (0.27)	-0.8 (0.15)***	192
Non-Energy Minerals	-3.3 (1.37)**	-1.1 (1.08)	-0.9 (1.6)	-1.8 (0.85)**	191
Commercial Services	-0.1 (0.32)	-0.3 (0.28)	0.3 (0.32)	-0.5 (0.21)**	166

The results in Table 7 clearly show the predicted size-effect: the effect of ESG on credit risk becomes more significant for larger firms. For both regression models, all coefficients in the Size 1 subset are insignificant. In the Size 2 subset, ESG-E (-0.8) and ESG-S (1-1.2) are the first coefficients to become significant. Finally, for Size 3, all variables over both models are significant. The Size 3 general ESG score is negative, indicating a negative relation to credit risk. Furthermore, the ESG sub-scores display similar, effects to previous results: Governance has a significant negative effect on credit risk, whereas Social scores have a positive, adverse effect on credit risk. Surprisingly, Environmental scores in large companies have a stronger negative relation to credit risk than Governance scores. This somewhat contradicts our full data set findings, which indicate that Environmental scores barely have a negative relation to credit premia.

Furthermore, the FEM and REM models results in similar coefficients, especially for larger firms (Sizes 2 and 3). For Size 1 firms, when both coefficients are insignificant, coefficients tend to differ, such as ESG being 0.2 and -0.3 for the FEM and REM models, respectively.

Table 7: Regression results investigating the effect of ESG on credit risk across three company sizes based on market value (in USD). For both FEM and REM models, the table shows ESG coefficients of two separate regressions: one using the general ESG score (Equation 7), and the other using ESG sub-scores (Equation 8). All regressions use debt-equity ratio (DE) and volatility (Vol) as control variables, which are not displayed. Standard errors are noted in parentheses. P-values are noted as: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Fixed-effects regression					
Market value (USD)	**ESG**	**ESG-E**	**ESG-S**	**ESG-G**	**n**
All	-0.3 (0.27)	0 (0.24)	0.5 (0.27)*	-0.3 (0.16)*	2343
Size 1 (0-10 bn)	0.2 (0.5)	0.5 (0.5)	0.1 (0.59)	-0.1 (0.33)	839
Size 2 (10-40 bn)	-0.3 (0.43)	-0.8 (0.38)**	1.2 (0.38)***	-0.1 (0.25)	906
Size 3 (40+ bn)	-0.4 (0.21)*	-0.4 (0.17)**	0.6 (0.18)***	-0.3 (0.11)**	537
Random-effects regression					
Market value (USD)	**ESG**	**ESG-E**	**ESG-S**	**ESG-G**	**n**
All	-0.6 (0.26)**	-0.1 (0.24)	0.3 (0.26)	-0.3 (0.16)**	2343
Size 1 (0-10 bn)	-0.3 (0.48)	0.4 (0.48)	-0.1 (0.57)	-0.4 (0.32)	839
Size 2 (10-40 bn)	-0.5 (0.39)	-0.8 (0.35)**	1 (0.36)***	-0.2 (0.23)	906
Size 3 (40+ bn)	-0.5 (0.2)**	-0.5 (0.16)***	0.5 (0.18)***	-0.3 (0.11)**	537

7 Concluding remarks

In this final section we first discuss our results and test our hypotheses. Next, we discuss research limitations and possibilities for further research, and finish with a general conclusion.

7.1 Discussion of results

Hypothesis 1 expects a negative relation between ESG scores and credit default swap premia. Although it is is difficult to conclusively generalize the effect of ESG scores on credit risk, the results of our regressions (Table 3) show that companies with higher ESG scores generally have lower CDS premia. More specifically, per unit increase of ESG score, a firm's CDS spread approximately decreases by 0.3 basis points, ceteris paribus. We therefore conclude that increased ESG scores have a negative, but financially positive, effect on credit risk.

Our second hypothesis covers the effects of ESG sub-scores: we expect to find a significant, negative ESG-G coefficient and lesser or insigificant ESG-E and ESG-S coefficients. The results in Table 4 show the negative effect of Governance on credit risk to be most significant and pronounced. This ESG-G effect is repeatedly observed over various models splits and thus confirms Hypothesis 2. We hypothesize that Governance metrics are primarily compliance and trust related, thus firms that are not compliant or trustworthy are deemed to be less credit-worthy, and vice versa. The Environmental sub-score consistently has a non-significant, slightly negative effect, with the exception for larger firms (40+ billion USD market size) showing a significant and strong negative effect. We therefore infer that increased Environmental efforts are generally not taken into account when evaluating credit risk, except for large firms. Third, the Social sub-score generally has an adverse effect on credit risk, that is, increased Social scores increase CDS premia. These results, however, are not consistently significant and are therefore not conclusive. We hypothesize that this adverse effect is caused by cost increase due to social efforts: e.g. related to employee compensation or training and development. The increase in costs can potentially decrease profitability, therefore increasing credit risk.

Hypothesis 3 expects the effect of ESG on credit risk to differ significantly across countries and sectors. Furthermore, we expect a stronger negative effect of ESG scores on credit risk for larger companies, i.e. a size effect. The country effects shown in Table 5 mainly display insignificant results, or results that are generally consistent with the full data set. Two exceptions are countries France and Spain; France is the only country to result in a significant positive ESG coefficient. The subset containing only French companies is reasonably balanced regarding sector, which provides extra incentive to further investigate the cause of this relation. Spain, on the other hand, displays unusually large, significant ESG and ESG-G coefficients. We hypothesize that these strong negative relations are caused by most Spanish companies in our set being (partly) government-owned. The sector effects shown in Table 6 do not show results that differ significantly from full data set results. We therefore conclude the effect of ESG on credit risk does not significantly differ across countries and sectors, (partly) falsifying Hypothesis 3. We do, however, confirm the Hypothesis 3 size effect, as Table 7 shows the negative effect of ESG (sub-)scores on credit risk is more pronounced and significant for larger firms (40+ billion USD market value). We hypothesize that this effect is caused by larger firms having increased public exposure and stakeholder pressure. These firms therefore endure more scrutiny and are thus more likely to focus on sustainability efforts. Furthermore, larger firms are likely to have more resources to allocate to sustainability efforts.

The research applies also two panel regression models: fixed-effects and random-effects. Although we do not explicitly cover or compare these models in the form of a research question or hypothesis, we now briefly touch upon the observed differences and similarities. First, the number of groups and number of observations per group in our data set better suit the FEM model (Nikolakopoulou et al., 2014; Clark and Linzer, 2012). Next, the models have shown to result in relatively similar regression coefficients and standard errors for larger sample sizes but differ significantly regarding p-values, as FEM coefficients generally are more significant. Furthermore, FEM outperforms REM in terms of R^2 (0.31-0.53), compared to REM (0.15-0.17). We therefore conclude that a fixed-effects model is a better fit for our data set. Strictly speaking, if the fixed-effects model is the true data-generating process, all random-effects results are inconsistent. This does not, however, change our prior conclusions regarding Hypotheses 1 to 3. Overall, we show that differences *within* firms (fixed-effects) are of better use in this research, opposed to differences *between* firm.

7.2 Limitations and future research

A main limitation in the research was data availability. Due to the use of credit default swaps as a proxy for credit risk we were only able to use a fraction of all available ESG data. For future research, it is advised to use a more abundant proxy for credit risk, such as credit ratings. This would increase the size of the data set significantly, making the set less imbalanced and (subset) results more reliable. Broadening the research scope to non-EU regions (e.g. United States or Asia) is another way to increase data set size.

Next, the main goal of the research was to investigate the general effect of ESG (sub-)scores on credit risk. Therefore, we have not thoroughly investigated the influence of some statistical issues such as autocorrelation and multicollinearity, amongst others. It is advised that future research further investigates these issues, which could for example be addressed by using a two-way time-fixed-effects model, clustered standard errors, or by including lagged y-variables in panel regressions. Related to time series analysis: the research does not provide evidence if the negative effect of ESG on credit risk is also a causal effect. That is, does an increase in ESG score cause a decrease in CDS premia, or do high ESG performers generally have lower CDS premia? To further investigate causation one could, for example, investigate ESG and CDS momentum and tilt.

Furthermore, several new hypotheses are raised in the discussion of results (Section 7.1), providing possible (business) explanations for our results. All newly raised hypotheses are not supported by literature and are to be investigated in further research.

Moreover, the Arabesque data set also provides sub-scores for the ESG sub-scores. These "sub-sub-scores" are shown in Appendix A.1, e.g. "business ethics" within Governance. Future research could therefore further deep-dive in and pinpoint the effects of sustainability using these sub-sub-scores.

Finally, the overall R^2 of our models is low (FEM: 0.31-0.53, REM: 0.15-0.17). Adding more control variables could potentially increase the true explanatory power of the model and better quantify the interpretation of the ESG regression coefficients.

7.3 Conclusion

Overall, the research is successful in investigating the effect of ESG scores on credit risk. We conclude that companies with high ESG scores generally have lower credit default swap premia, and vice versa. More specifically, per unit increase of ESG score, a firm's CDS spread approximately decreases by 0.3 basis points, on average (ceteris paribus). Within ESG sub-scores, the Governance score has the most significant negative effect on credit risk. The Environmental sub-score has shown to be of negligible influence and the Social score appears to have an (insignificant) adverse effect on credit risk, increasing credit premia. No significant differences in the effects of ESG scores on credit risk are found across European countries or sectors, with the exception of France and Spain. We do, however, observe that the negative effect of ESG on credit risk is greater and more significant for larger firms (40+ billion USD market value). Finally, we conclude that differences *within* firms best explain the CDS-ESG relation for our panel data, that is, using fixed-effect panel regression models opposed to random-effect models.

Future research on the topic is to determine if the observed effects of ESG on credit risk are truly casual or merely correlative, and following research can also further investigate our newly raised hypotheses that provide initial (business) explanations for our results. In conclusion, the research posits several interesting conclusions and topics for further research on sustainability and credit risk, and provides rationale for increased ESG integration in risk management for European corporates.

A Appendix

A.1 ESG sub-score breakdown

Table 8: A breakdown of criteria used by Arabesque (ESG ratings provider) to evaluate ESG sub-scores.

	ESG	
Environment (ESG-E)	**Social (ESG-S)**	**Governance (ESG-G)**
Environmental Management	Compensation	Business Ethics
Environmental Solutions	Diversity	Capital Structure
Environmental Stewardship	Employment Quality	Corporate Governance
Resource Use	Human Rights	Forensic Accounting
Waste	Labour Rights	Transparency
Water	Occupational Health and Safety	
	Product Access	
	Product Quality & Safety	
	Stakeholder Relations	
	Training & Development	

A.2 Overview of companies

Table 9: An overview of all 106 companies included in the full data set. The companies are distributed over 16 European countries and 16 sectors.

#	Company	#	Company	#	Company
1	Abertis Infraestructuras SA	41	Glencore plc	81	Sodexo SA
2	Accor SA	42	HeidelbergCement AG	82	Solvay SA
3	Adecco Group AG	43	Heineken Holding N.V.	83	SSE plc
4	Adidas AG	44	Hellenic Telecommunications SA	84	Stagecoach Group plc
5	Air France-KLM SA	45	Iberdrola SA	85	STMicroelectronics NV
6	Akzo Nobel N.V.	46	InterContinental Hotels Group PLC	86	Stora Enso Oyj Class R
7	Alstom SA	47	ISS A/S	87	Suedzucker AG
8	Anglo American plc	48	ITV PLC	88	Svenska Cellulosa Aktiebolaget
9	ArcelorMittal SA	49	J Sainsbury plc	89	Swisscom AG
10	ASSA ABLOY AB	50	Kering SA	90	Syngenta AG
11	AstraZeneca PLC	51	Kingfisher Plc	91	TDC A/S
12	Atlantia S.p.A	52	Koninklijke DSM N.V.	92	Technip SA
13	Atlas Copco AB Class A	53	LANXESS AG	93	Telefonaktiebolaget LM Ericsson
14	BASF SE	54	Linde AG	94	Telefonica SA
15	Bayer AG	55	Melia Hotels International, S.A.	95	thyssenkrupp AG
16	Bayerische Motoren Werke AG	56	Metsa Board Oyj Class B	96	Transneft PJSC Pref.
17	BP p.l.c.	57	National Grid plc	97	TUI AG
18	British American Tobacco p.l.c.	58	Neste Corporation	98	Unilever PLC
19	Casino, Guichard-Perrachon SA	59	Next plc	99	United Utilities Group PLC
20	CIR Compagnie Industriali Riunite SpA	60	Nokia Oyj	100	UPM-Kymmene Oyj
21	Clariant AG	61	NXP Semiconductors NV	101	VINCI SA
22	Compagnie de Saint-Gobain SA	62	OMV AG	102	Vodafone Group Plc
23	Compass Group PLC	63	Persimmon Plc	103	Volkswagen AG Pref
24	Continental AG	64	Pirelli & C. S.p.A.	104	Volvo AB Class B
25	CRH Plc	65	ProSiebenSat.1 Media SE	105	Wm Morrison Supermarkets plc
26	Daily Mail & General Trust plc Class A	66	Rallye SA	106	WPP Plc
27	Danone SA	67	Rank Group Plc		
28	Deutsche Lufthansa AG	68	RELX PLC		
29	Deutsche Post AG	69	Renault SA		
30	Diageo plc	70	Rentokil Initial plc		
31	Edison Spa Az. di risp. non conv.	71	Repsol SA		
32	EDP Renovaveis SA	72	Rio Tinto plc		
33	Electricite de France SA	73	Royal Dutch Shell Plc Class B		
34	EMIS Group plc	74	RWE AG		
35	EnBW Energie Baden-Wurttemberg AG	75	Sanofi		
36	Endesa S.A.	76	Securitas AB Class B		
37	Eni S.p.A.	77	Siemens AG		
38	EVN AG	78	SKF AB Class B		
39	Fresenius SE & Co. KGaA	79	Smiths Group Plc		
40	GlaxoSmithKline plc	80	Smurfit Kappa Group Plc		

A.3 Data sampling distribution

Table 10: An overview of the sampling distribution per country, sector, year, quarter and size; n represents the number of observations. Only subsets containing $n > 150$ are used in the subset regression analysis (see Section 5.3.2). Size is based on company market value in US Dollars ($).

Country	**n**	**Sector**	**n**
United Kingdom	647	Process Industries	255
Germany	424	Utilities	250
France	285	Producer Manufacturing	215
Sweden	168	Consumer Services	200
Spain	150	Consumer Non-Durables	192
Switzerland	133	Non-Energy Minerals	191
Netherlands	120	Commercial Services	166
Finland	111	Energy Minerals	144
Italy	89	Retail Trade	122
Ireland	47	Health Technology	112
Austria	38	Communications	111
Denmark	37	Consumer Durables	108
Belgium	24	Transportation	101
Greece	24	Electronic Technology	96
Luxembourg	24	Industrial Services	65
Russian Federation	22	Technology Services	15
Year	**n**	**Quarter**	**n**
2015	386	1	585
2016	380	2	589
2017	405	3	588
2018	407	4	581
2019	393		
2020	372		
Size	**n**		
Size 1 (0-10 bn)	839		
Size 2 (10-40 bn)	906		
Size 3 (50+ bn)	537		

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