Master's Degree Dissertation

Universitat Pompeu Fabra BSM

What is the Relationship between Digitalization and Profitability of Banks in the Eurozone, and how is it moderated by Corporate Sustainability?

A two-step approach to analyzing digitalization in the banking sector.

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Abstract

In recent years, banks in the Eurozone have been facing a challenging market environment causing them to struggle with profitability. In an attempt to improve performance, many banks have indulged in digitalization strategies. However, it is still unclear to what extent digitalization efforts drive profitability. This paper investigates as a first step the relationship between digitalization and profitability in the banking sector. As a second step, the moderating effect of corporate sustainability is examined. Using a sample of 54 listed banks within the Eurozone over the period 2012-2021, we determine a cost-efficiency frontier to retrieve the technological gap for each bank per year. Through innovation, banks can reduce the technological gap. Because innovation in the banking sector is mainly caused by technological change, the sustained improvement of the technological gap is taken as a proxy for digitalization.

Regressing digitalization on the profitability measurements ROE and ROA shows that digitalization does not have a consistently significant correlation with bank profitability. This indicates that without other factors, banks face a profitability paradox in the sense that digitalization is not a guarantee for improved profitability.

However, including different corporate sustainability metrics in the regression, it appears that the controversies score acts as a moderator. Consequently, this indicates that banks can materialize their digitalization efforts by being involved in fewer controversies and hence improving their reputation and customer trust.

Keywords: Digitalization; Profitability; ESG; Corporate Sustainability; Frontier; Efficiency; Technological Gap; Reputation; Banking Industry

Chapter 1

Introduction

During the last years, the European banking sector has been marked by negative interest rates, the ongoing Brexit, and slow economic growth. While European banks are struggling with profitability (Statista, 2019), the overall online banking penetration in the Euro Area was at a bare level of 61% in 2019, and some of its most advanced economies situated themselves even below this average, such as Germany with 50% (Statista, 2021).

While banks are facing fading profitability, the fintech industry has been rising and competition from app-only banks is capturing a growing part of the market (Statista, 2022). Banks suffer a client exodus towards alternative options of banking, whereas Covid-19 has led companies to focus on their digital transformation strategies and accelerated the adoption of digital media (Statista, 2020).

In order to catch up with their competition and the unfavorable market conditions, it seems that banks need to ramp up their service offering, all while cutting costs. It is specifically in this setting that the question arises whether digitalization actually has a positive relationship with profitability and whether there are unobserved external factors influencing the effectiveness of their digitalization efforts.

1.1 Contribution and Objective

While there has been extensive research on the impact of digitalization on banks, most studies have relied on data from the United States or from emerging markets. Recent literature provides only a handful of comparable studies focusing on the European banking sector. One paper examined the relationship between Corporate Sustainability (CS) and digitalization on large banks in developed countries for the time period of 2003-2016 (Forcadell et al., 2020). However, the majority of these banks were not from the Eurozone. This paper will focus on banks of all sizes within the Eurozone and for the later time frame of 2012-2021.

This paper seeks to analyze whether CS might moderate the relationship between digitalization and profitability. There are several factors leading to this assumption. First, reputation and trust, which are to a large extent generated by CS, were identified by literature as crucial drivers of clients' adoption of digital banking efforts (Forcadell et al., 2020). A paper from Deloitte mentions that stickiness to banks, especially from younger customers, is at risk. Key factors to increasing customer retention are trust in the digital content, as well as consistent and transparent communication (Deloitte, 2021).

The objective of this report is to determine whether there is a significant relationship between digitalization and banking profitability in recent years in the Eurozone. In addition to this, this paper seeks to answer the question of whether CS has a moderating effect on the before-mentioned relationship.

1.2 Report Outline

In the following section, a literature review is laid out to analyze and give an initial understanding of banking digitalization, its measurement methods, and its influences on banking profitability. The same analysis is laid out for CS, as well as how it connects to digitalization. We find ambiguous evidence regarding the impacts of digitalization on performance. A conceptual framework is based on the literature review and demonstrates how CS may moderate the relationship between digitalization and profitability.

After presenting our hypotheses and conceptual framework, a subsequent part will give guidance about the used methods by referencing previous studies, and outline how each hypothesis will be answered. To answer the main research questions, we collected a sample of 54 banks in 14 countries in the Eurozone. Our computations used the fixed effect regression model since it is a good fit for panel data, namely as it controls for individual characteristics.

A results section will show and analyze the obtained regression results, which confirm that digitalization has a significant positive relationship with ROE, but shows an insignificant relationship with ROA. Finally, different variables are introduced as CS moderators into the regression. An interesting contribution to literature is a particularly significant outcome for the controversy score, which is, under our knowledge, an insofar unobserved factor in the relationship between banking digitalization and profitability.

We end the report with a final discussion of our results, as well as implications for further research.

Chapter 2

Literature Review

There has been extensive research about the impact of digitalization in the banking sector. This section will review some important papers about digitalization and CS. It will conclude with the derived hypotheses and conceptual framework.

2.1 Digitalization

As a first step, we need to identify and define what exactly is considered digitalization. Scholz argued that the digital age began after the moment when digital storage capacity became larger than the analog one, which happened to be in the year 2002. He outlines the type of knowledge representation (analog vs digital), the increased abilities to collect, manipulate and interpret large streams of data, and its transmission form, as the key elements of digitalization (Scholz, 2017).

2.1.1 Digitalization in the banking sector

Digitalization in the financial sector has been apparent, especially since the financial crisis, and has ever since been evolving rapidly. A global reshaping of the industry has allowed banks and other financial institutions to deploy technological changes. By the year 2020, the financial services industry has the largest investments in IT per user across industries (Carbó-Valverde et al., 2020). Technological advances have allowed firms in the financial sector to use digital media strategies such as multi-channels (digital banking), data collection (big data), data management, artificial intelligence (Robo-advisors), blockchain (cryptocurrencies), and crowd-lending platforms. Several related infrastructures have been established, some examples are the 5G network, cloud computing, and machine learning (OECD, 2017).

Filotto et al. mention the difference between traditional and direct banking. They describe traditional banking as approaches based on physical interaction with customers, hence in person and through branches of the bank. Whereas direct banking involves digital channels which are directly accessed by customers without the intervention of bank employees (Filotto et al., 2021).

Another factor leading to a broad digitalization of the banking sector is the wide adoption of technologies amongst their customers. Customers use digital services if they judge them as safe (Casaló et al., 2007) and convenient (Laukkanen, 2016). There are several factors that affect digitalization, such as age (Estrella-Ramon et al., 2016-10-03) and geographic location (Xue et al., 2011). Amongst others, customer data can be leveraged to increase performance in areas such as consumer behavior prediction (George et al., 2014), customer relationships and lending activities (Davenport & Dyché, 2013) and efficient allocation of internal resources (Brenner, 2018).

2.1.2 Need for Digitalization

Dadoukis et al. argued that the nature of the global crisis, being unexpected and exogenous to the financial system, has favored banks involved in higher IT spending prior to the shock. The author's hypothesis is that banking institutions investing more of their resources into IT systems have assured investors of their capability to create value even in times of high uncertainty. They proved in their study the ability of banks involved in higher technology investments to withhold a stronger position during a crisis when compared to their less technologically sophisticated counterparts. They also outlined the view that digitalization could serve as a possible instrument to foster financial stability during crisis times (Dadoukis et al., 2021).

M. de la Mano and Padilla argue that BigTech, by leveraging their dominant positions in social media, cloud computing, and data sharing, could enter banking markets more aggressively and become a possible threat to incumbent banks (de la Mano & Padilla, 2019).

2.1.3 Digitalization and Profitability

Besides the previously mentioned competitive advantages of digitalization, Forcadell mentioned the potential to decrease asymmetric information between banks and their customers through digital environments. The asymmetric information describes the fact that the borrower is more aware than the lender about the chance of meeting the contract conditions. He argues that digital environments, hence eBanking or digitalization in general, allow decreasing the cost of information, and hence soften the information asymmetries on the part of the banks (Forcadell et al., 2020). Other factors leading to enhanced profitability are related to better customer service, quicker interactions with customers (Gupta et al., 2018) and risk mitigation (Dadoukis et al., 2021).

Even though some papers indicate that digitalization has a positive effect on banks' profitability, some authors point out a phenomenon called the "productivity paradox". The productivity paradox was outlined for the first time by Solow in 1987. He identified in his paper that IT expenditures did not have a positive effect on companies' productivity (Solow, 1987). In 2001, McKinsey Global Institute confirmed the presence of the productivity paradox in the US and European banking sector for a period considering the five years prior to 2001 (Institute, 2001). Another paper found the productivity paradox in relation to different kinds of IT spending, where IT services from external providers showed a positive influence on profitability, and acquisitions of hardware and software decreased profit efficiency (Beccalli, 2007).

2.1.4 Measurement of Digitalization

Dadoukis et al. measured the degree of technology adoption by measuring the total ratio of spending of banks on tech and communication expenses and creating a dummy variable. They divided banks into above median (high) and below-median to discriminate between tech adopters and laggards (Dadoukis et al., 2021).

Alsmadi et al. measured eBanking activities by creating a dummy variable which equals 1 if the banking institution has adopted eBanking, and 0 otherwise (Al-Smadi & Al-Wabel, 1970).

Beccalli used balance sheet data in her study to collect data concerning banks' IT spending, more precisely spending in hardware, software, and other IT service areas. Her study was different from several previous studies insofar that she measured operational productivity with X-efficiency. Her reasoning includes that the frontier obtained through this computation incorporates different indirect aspects of IT investments, such as quality, customer satisfaction, responsiveness, and product variety (Beccalli, 2007).

Another approach for measuring digitalization is presented by Forcadell. The paper explains how accounting data is used to compute a frontier and retrieve technological gaps. The further an entity situates itself from the frontier, the lower its cost efficiency and consequently its degree of digitalization. These efficiency scores are converted into proxies for digitalization by using the sustainable improvement of these scores. (Forcadell et al., 2020).

Using a stochastic frontier analysis to measure efficiency in banks is a commonly used method (J. Bos & Schmiedel, 2007)(Badunenko & Kumbhakar, 2017). However, using this method to measure digitalization is relatively new. The advantage is that it relies on accounting data that is standardized and available for a large number of banks.

The theory behind this approach is that when calculating an efficiency approach, the returned distance to this frontier, the technological gap, can be improved through innovation (J. W. Bos et al., 2013). In the banking industry, innovation occurs mainly through technological change and thus digitalization (Forcadell et al., 2020). Fintech has been found to operate closer to the cost efficiency frontier by using the latest technology while traditional banks show lower cost efficiencies (Lee et al., 2021). Based on the ability of technology and digitalization to reduce costs we can, therefore, use the change in the technological gap as a proxy for digitalization.

2.2 CS in Banking

There are many definitions for corporate social responsibility (CSR) and corporate sustainability (CS). Sometimes these terms are used interchangeably and sometimes they are defined differently. Montiel (2008) and Swarnapali (2017) both mention that even though CSR and CS have different backgrounds they are converting to the same concept and can be used as synonyms, especially in more recent studies. Another paper identified five common dimensions of CSR but also concluded that the real challenge is not the definition of CSR but understanding how it is socially constructed in a specific business context (Dahlsrud, 2008). A common approach is to define CSR as "A concept whereby companies integrate social and environmental concerns in their business operations and in their interaction with their stakeholders on a voluntary basis" (Commission of the European Communities, 2001).

2.2.1 Measuring CS

With CS becoming more important in the last years there was a surge of different sustainability reporting tools, such as frameworks, standards, and ratings made by a third party that evaluates the CS or ESG performance. The advantage of external ratings is that they are standardized in the applied criteria and calculation methodology. Consequently, they allow for a better comparison of the sustainability performance of entities (Siew, 2015).

One of these ratings is the ESG score from Eikon Refinitiv. Refinitiv provides an ESG score between 0 and 100 as well as a grade from D to A. They use more than 630 ESG metrics from which 186 comparable measures are used for calculating the scores of the different ESG categories. The data is updated in line with companies' ESG disclosure which in most cases is once a year. While the environmental pillar includes the use of resources and emissions, the social pillar includes workforce and community metrics, and the governance pillar metrics for management, CSR strategy, and transparency (Refinitiv, 2022).

In addition to the normal ESG score Refinitiv also measures controversies. The controversies are updated the moment they occur and reported by the media. A company without controversies will have a score of 100. In the presence of controversies, the weight of the controversy is factored in and they are benchmarked on an industry group basis (Refinitiv, 2022).

2.2.2 Digitalization and CS

The connection between CS and digitalization seems to be less obvious at first. The paper by Forcadell et. al. suggests that the positive effects of digitalization and CS on performance are only realized if both elements are executed simultaneously (2020). This paper claims that the higher the CS reputation of a bank is, the higher will be the impact of its digital strategies (Forcadell et al., 2020).

As research has shown CS can decrease information asymmetries in favor of customers because of higher transparency and reliability while at the same time reducing the chances of opportunistic behavior of the bank (Hoepner et al., 2016).

At the same time technology reduces information asymmetries in favor of the banks as they know more about their customers. Consequently, this causes an increase in information asymmetries on the customers' side. This can be offset by a high level of CS through the improved reputation and trustworthiness of the bank.

This article also concludes that CS investments alone enhance efficiency but do not have a positive impact on market performance if not accompanied by a digitalization strategy. The combination of a CS and digital strategy can also create a competitive advantage that results in better performance.

Some negative consequences of digitalization are that customers might feel more vulnerable about privacy issues and others might struggle with technological changes causing the digital gap to become wider. Furthermore, digitalization often results in job displacement. All of these can harm the bank's reputation which can be compensated with a CS-based positive reputation (Forcadell et al., 2020).

2.3 Conceptual Framework

Based on the reviewed concepts the following hypotheses can be derived:

H0 = There is no relationship between digitalization and bank profitability.

H1 = There is a positive relationship between digitalization and bank profitability.

H2 = There is a positive relationship between digitalization and bank profitability in the presence of ESG metrics.

H3 = CS, measured by ESG metrics, moderates the relationship between digitalization and bank profitability.

These hypotheses are illustrated in the following figure 1.

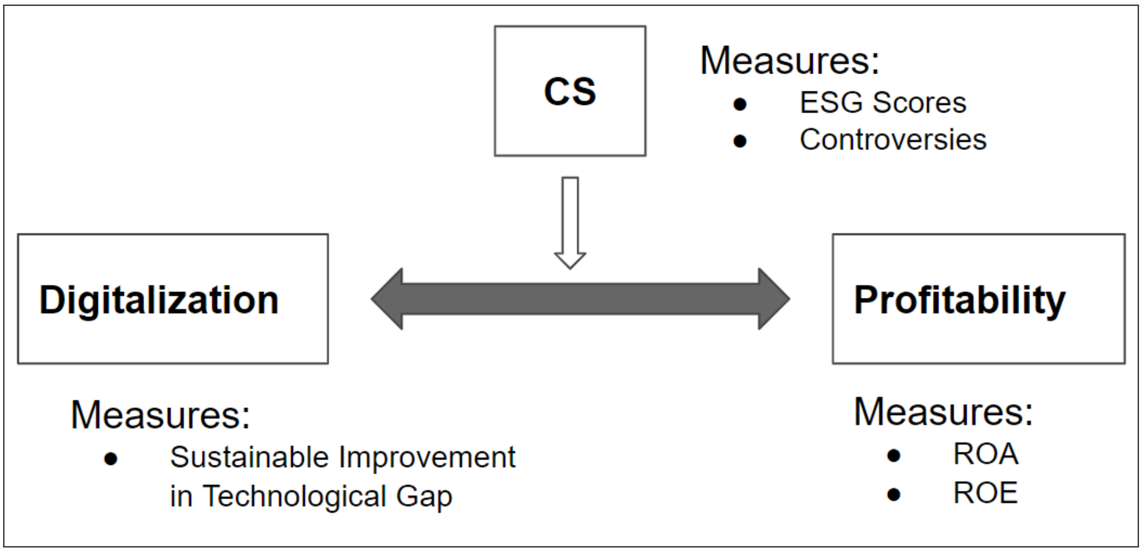

Figure 1: Conceptual Framework.

Chapter 3

Methods

This chapter will outline the applied methods to explore the relationship between digitalization and banking profitability.

3.1 Sample

Using the Thomson Reuters database we collected a sample of 54 listed banks headquartered in the Eurozone, as defined by the Thomson Reuters Business Classification (TRBC), excluding central banks. The availability of financial data on Refinitiv Eikon was crucial for the sample selection. The sample was collected for the years 2012 to 2021. This led to an initial panel data set with 673 observations.

3.2 Variables

3.2.1 Dependent Variables

To measure profitability we will use the two measures return on equity (ROE) and return on assets (ROA). Both are based on accounting data and commonly used in literature to measure profitability (Rahman et al., 2015).

3.2.2 Independent Variables

Our independent variables are digitalization and CS. The measurement for digitalization is based on the theory that digitalization can help banks to control and reduce costs (Frame & White, 2004). As an estimation for digitalization, we first determine the gap to the frontier, measured by the efficiency scores obtained from the stochastic frontier. The final digitalization variable $DIGI$ is the relative change of the efficiency score conditional on a two-year consecutive improvement. This is based on the approach used by Forcadell et al. (2020).

CS is measured in different ways. First, we take the overall ESG scores from Thomson Reuters and use them directly in our model as ESG. Additionally, we will include several ESG metrics, more precisely Environment, Social, Governance, and the Controversies score, as separate variables.

3.2.3 Control Variables

Literature has identified several factors that may impact profitability, and different papers investigating the performance of banks have shown a consensus on applicable control variables. To increase the meaningfulness of our model, we decided to control for the following factors:

The first control variable is $CreditRisk$. Serving as a proxy for the health of a bank's portfolio, the ratio of non-performing loans to total loans is commonly used in literature as an indicator for credit risk (Rahman et al., 2015).

A second option is the ratio of total equity divided by total assets. The equity ratio is widely used in literature when evaluating banks' performance in order to account for different risk profiles (Hughes & Mester, 1993), (J. W. Bos et al., 2013), namely capital structure and bank risk (Berger & Bouwman, 2013).

The $CreditRisk$ and the equity ratio are highly correlated, so for our model, we decided to only use the $CreditRisk$ ratio.

Different articles proved that firm size is an important explanatory variable in determining banking performance. As the literature suggests, we took the logarithmic transformation of total assets to measure the size effect and named it $Size$ (Hossain & Saif, 2019) (Chhaidar et al., 2022).

As the third control variable, we included $CAR1$, the Tier 1 capital adequacy ratio. This ratio has been used in several articles as further assessment of solvency risk (Forcadell et al., 2020), and generally as an indicator for the quality of bank capital (Scholtens, 2009).

Some studies also include the debt to equity ratio to control for leverage. However, there is no general consensus about its performance on banking performance. Saeed et al. showed a negative relationship between long-term debt and ROA, ROE, and EPS (Saeed et al., 2013), whereas Taani et al. proved that total equity has no significant effect on the ROE in the banking industry (Taani, 2013).

As the last control variables, we include the years as dummy variables to control for year-specific effects on profitability.

3.3 Frontier

To estimate digitalization we first need to retrieve the technical efficiency scores. To retrieve these scores for each observation and each year, we estimated a frontier with a time trend. Due to the limited number of banks per country, it was not reasonable to calculate a frontier per country per year.

The model for the frontier is based on the banking intermediation approach that takes banks as intermediaries between borrowers and lenders. This approach is frequently used in literature to estimate frontiers in the banking sector (J. Bos & Schmiedel, 2007). Under this approach, we take $NetLoans$ as output, and *Labor* and $NonInterestExpense$ as input variables. Simultaneously, we control for leverage by using the *DebtEquity* ratio and also include the time trend "$Year$" (Forcadell et al., 2020).

The following lines show the frontier equation and the retrieval of efficiencies by using the "Frontier" package in R.

$$FrontierYear <- sfa(log(NetLoans)\ log(LaborAndRelatedExpense)$$

$$+log(NonInterestExpense) + DebtEquity + Year, data = Yeardata)$$

$$te <- efficiencies(FrontierYear)$$

To include as many observations as possible a new data frame with only the relevant variables for the frontier is created before cleaning and filtering the data. This leads to a data set with 527 observations of 54 banks (table 1). To all variables in the frontier, logarithms are applied, unless the variable is a ratio, to avoid problems of non-stationarity.

Table 1: Sample Distribution: Number of Banks and Observations per Country (2012 - 2021).

Year	Banks	Observations
Austria	5	47
Cyprus	3	30
Finland	3	30
France	13	128
Germany	4	40
Greece	3	30
Ireland	2	20
Italy	8	74
Lithuania	1	10
Malta	1	10
Netherlands	2	20
Portugal	2	20
Slovenia	1	9
Spain	6	59
Sum	54	527

Figure 2 shows the frontier output from R and table 2 shows the basic characteristics of the obtained efficiency scores.

```
final maximum likelihood estimates
                             Estimate  Std. Error z value  Pr(>|z|)
(Intercept)               -20.2634485  15.3048909 -1.3240   0.18551
log(LaborAndRelatedExpense)  1.1541592   0.0372754 30.9630 < 2.2e-16 ***
log(NonInterestExpense)     -0.2033925   0.0364108 -5.5861 2.323e-08 ***
DebtEquity                   0.0039115   0.0028527  1.3711   0.17033
Year                         0.0129506   0.0075945  1.7053   0.08815 .
sigmaSq                      0.4796517   0.0460868 10.4076 < 2.2e-16 ***
gamma                        0.7245378   0.0504500 14.3615 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
log likelihood value: -385.425
```

Figure 2: Frontier Output from R.

Table 2: Efficiency Scores.

Min. :	0.1770
1st Qu.:	0.6036
Median :	0.7003
Mean :	0.6677
3rd Qu.:	0.7575
Max. :	0.9163

With the efficiency scores from the frontier, we can now calculate the relative yearly changes. We can observe varying changes per year. In other words, there is not always an improvement causing our digitalization variable to be zero in many cases.

3.4 Model Specification

As we will analyze variables with a set of multiple features over multiple years, the choice of potential models widely used in literature can already be limited to some main models.

Which model to choose depends on several factors; one of them being the presence of endogeneity, which is generally described as the correlation between explanatory variables and the error term (Wooldridge, 2010). Endogeneity might appear in case there is an unobserved effect ("Omitted Variable Bias") or in case the endogenous variable is itself a predictor of the exogenous variable and not simply a response ("Simultaneity Bias") (Lynch & Brown, 2011).

In case that unobserved effects are correlated with included variables, the exogeneity assumption of the Gauss-Markov theorem is violated and the pooled OLS, which is commonly used to analyze panel data, might be inconsistent.

The reason to choose fixed effects over a pooled OLS regression is that it accounts for panel data structure while controlling for unobserved effects per bank that may influence the dependent variable and thus reducing the omitted variable bias. As the fixed effects model removes time-invariant characteristics, it is possible to assess with more accuracy the effect of the predictive variables on the dependent variable.

Table 3: Model Specification.

Sanity Check
$Profitability_{it} = CreditRisk_{it} + Size_{it} + CAR1_{it} + Year + \alpha_i + u_{it}$
H1 Positive relationship between digitalization and bank profitability
$Profitability_{it} =$
$DIGI_{it} + CreditRisk_{it} + Size_{it} + CAR1_{it} + Year + \alpha_i + u_{it}$
H2 Positive relationship of digitalization, ESG and bank profitability
$Profitability_{it} =$
$DIGI_{it} + ESG_{it} + CreditRisk_{it} + Size_{it} + CAR1_{it} + Year + \alpha_i + u_{it}$
H3 ESG metrics moderate the relationship
$Profitability_{it} = DIGI_{it} + ESG_{it}$
$+(DIGI * ESG)_{it} + CreditRisk_{it} + Size_{it} + CAR1_{it} + Year + \alpha_i + u_{it}$

→ Where i indicates the entity and t the time and α are the entity-specific intercepts. $Year$ indicates dummy variables to control for each year. u_{it} is the error term. ESG is a placeholder for various ESG metrics.

As shown in table 3, we will do a sanity check and a standard profitability regression with fixed effects. After a fixed-effects regression including our digitalization proxy, we will run fixed effects regressions for the ESG data set including the digitalization proxy, and the ESG metrics. In a final step, we include the interaction between ESG and digitalization to check whether ESG might behave as a moderator.

3.5 Data Exploration and Cleaning

After calculating the efficiency scores with the frontier, the obtained data set contains 527 observations. However, as we add the controls and variables for ESG, we observe that not all variables have 527 observations. This indicates a large number of missing values for some variables.

With the calculated digitalization variables from the frontier, we can start developing the regression models. As we calculate the sustained relative change in the efficiency the first values are in 2014. For these reasons, we need to exclude the years 2012 and 2013 from the regression which reduces the data set to 427 observations.

Dropping missing values related to the control variables leads to a final data set of 262 observations (table 4). For the second and third hypotheses, we also need to include the ESG parameters. ESG data was available for a significantly smaller number of banks which reduces our data set for these regressions to 148 observations (table 5).

We decided to not fill missing values because the imputation of the missing value relies on reasonable guesses for the missing data. However, missing data mostly occurred in the ESG scores, it is difficult to make reasonable guesses for these kinds of values especially because historical values were missing for consecutive years. In general, if data was missing, it was usually for a few years in a row and for the same entity. Hence, imputing data points with methods such as taking the average of an entity would potentially bias the data set.

Table 4: Descriptive Statistics Digitalization Set (N =262).

Variable	mean	std	min	max
Interaction	0.01	0.05	0.00	0.55
ROE	5.22	10.74	-46.70	77.44
ROA	0.43	0.95	-3.97	8.91
CAR1	15.20	4.19	8.15	31.93
CreditRisk	0.09	0.14	0.00	0.75
Size	25.16	1.85	21.54	28.60

Table 5: Descriptive Statistics ESG Set (N =148).

Variable	mean	std	min	max
Interaction2	0.01	0.05	0.00	0.55
ROE	3.63	10.07	-41.75	39.67
ROA	0.26	0.82	-2.42	6.14
ESG	59.98	15.43	19.22	89.62
ESGInteraction	0.04	0.09	0.00	0.62
Controversies	75.65	32.66	0.43	100.00
CAR1	13.70	2.80	8.15	28.56
Social	69.69	16.84	13.90	97.62
Governance	64.50	20.76	11.07	93.29
Environment	71.70	23.83	13.55	97.47
CreditRisk	0.12	0.16	0.01	0.75
Size	26.04	1.53	22.14	28.54
DIGIESG	0.76	3.74	0.00	38.09

Chapter 4

Analysis and Results

Taking a look at our sanity check regressions $S1ROE$ and $S2ROA$, we see that $CreditRisk$ is significant at the 5% level for both regressions. Its negative relation to the profitability measurements is in line with our expectations and literature, as a higher NPL ratio should add risk and potential losses to the business. The $Size$ has a negative effect on profitability, which is equal to the findings of a similar study (Forcadell et al., 2020), however, $Size$ is not significant at the 5% significance level. The effect of $CAR1$ is also in line with expectations but is only significant at the 10% significance level 6.

4.1 Is there a significant relationship between digitalization and bank profitability?

We first examine the base regressions ($A1$ and $A2$), which regress the dependent variable on the digitalization and control variables. Receiving an R-squared of 30.45% and 19.14% for ROE and ROA respectively, A1 explains 11.31% more of the variation of the respective Y variable than A2. At the 5% significance level, we can reject the null hypothesis for ROE and accept the alternative hypothesis that there is a positive relationship between digitalization and banking profitability based on our first regression output (table 6).

This is in line with the evidence in the literature that has shown that digitalization effort allows banks, for instance, to better predict consumer behavior and allocate internal resources more efficiently (George et al., 2014)(Brenner, 2018). However, for ROA the alternative hypothesis is rejected. This shows evidence of the profitability paradox because there is no clear positive correlation (Gupta et al., 2018). The reason for an insignificant relationship between digitalization and profitability may be because digitalization is a necessity rather than something that can provide a competitive advantage on its own.

Table 6: Regression Coefficients Sanity Check and Base Regression.

	Sanity Check				ROE		ROA	
	S1 ROE		S2 ROA		A1		A2	
	b	p-value	b	p-value	b	p-value	b	p-value
const	28.1115	0.1129	2.9137	0.1389	25.2572	0.1279	2.7728	0.1336
CreditRisk	-35.8372	0.0000	-2.5752	0.0000	-33.2775	0.0000	-2.4489	0.0000
Size	-0.8669	0.1578	-0.0959	0.1565	-0.7408	0.1966	-0.0896	0.1543
CAR1	0.1970	0.5114	0.0052	0.7678	0.1067	0.6541	0.0008	0.9689
Year.2015	2.1796	0.2943	0.1077	0.4425	2.0639	0.3128	0.1020	0.4573
Year.2016	2.7143	0.4375	0.3790	0.2751	2.7388	0.3938	0.3802	0.2521
Year.2017	-0.0927	0.9714	0.0924	0.6338	-0.7261	0.8073	0.0611	0.7530
Year.2018	0.2143	0.9264	0.2071	0.1586	0.0601	0.9796	0.1995	0.1741
Year.2019	-1.3953	0.5898	0.0916	0.5420	-1.3815	0.5736	0.0923	0.5391
Year.2020	-3.9363	0.2193	-0.0267	0.9198	-3.8652	0.1833	-0.0232	0.9301
Year.2021	-3.2525	0.2589	-0.1081	0.5432	-2.7429	0.3065	-0.0829	0.6449
DIGI					65.6373	0.0016	3.2397	0.2645
r-squared	23.07%		16.84%		30.45%		19.14%	

4.2 Digitalization and Profitability in Presence of ESG Metrics

As can be seen in table 10, regression $A6$ has slightly different results to $A2$, meaning that the reduction of the data set seems to have an impact on the ROA model. The coefficient is now negative but still insignificant. The digitalization coefficient in the model $A3$ based on ROE as a dependent variable is significant and shows a positive relationship with $DIGI$ on both data sets.

These results are in line with the productivity paradox, as digitalization partly has a significant and positive relationship with profitability (ROE), but on the other hand, has an insignificant relationship with ROA.

Correlation of ESG Metrics

Looking at the correlations between the ESG metrics, we observe a moderate positive correlation between the ESG pillars and the overall score. They differ slightly in the magnitude of the correlation. This is reasonable because Refinitiv assigns different weights to the different pillars adjusted for the industry type. For banks, higher weights are assigned to the governance and social pillars (Refinitiv, 2022).

The controversies scores are negatively correlated with the ESG pillars and positively but weakly correlated with the overall ESG score.

Table 7: Correlation Martix ESG metrics.

	ESG	**Controversies**	**Social**	**Governance**	**Environment**
ESG	1	0.2733	0.6076	0.6905	0.5065
Controversies	0.2733	1	-0.4601	-0.2555	-0.4285
Social	0.6076	-0.4601	1	0.6417	0.6596
Governance	0.6905	-0.2555	0.6417	1	0.5316
Environment	0.5065	-0.4285	0.6596	0.5316	1

Regressions Including different ESG Metrics

After the base model was tested on the new data, the different ESG metrics were included individually. The overall ESG score shows a significant and positive relationship with profitability but is only significant with ROE as the dependent variable 8.

While the three ESG pillars show no significance in both the ROE and ROA model, the controversies score is positive and significant in both models 8. The entire list of coefficients for the models can be found in the appendix 12. Other studies have found that an increase in controversies scores reduces the risk-taking of banks making them more stable (Galletta & Mazzù, 2022). However, this is not proving

Table 8: Regression Coefficients ESG Metrics.

		ROE				ROA	
		b	p-value			b	p-value
A4	ESG	0.1688	0.0062	A7	ESG	0.0092	0.1033
	DIGI	24.1481	0.0223		DIGI	-0.1338	0.8387
	r-squared	0.4028			r-squared	0.2294	
A4a	Environment	0.0498	0.6146	A7a	Environment	-0.0037	0.7627
	DIGI	21.8487	0.0987		DIGI	0.2832	0.8060
	r-squared	0.3498			r-squared	0.2081	
A4b	Social	0.0966	0.3103	A7b	Social	0.0030	0.7754
	DIGI	22.8914	0.0734		DIGI	-0.1291	0.8699
	r-squared	0.3578			r-squared	0.2052	
A4c	Governance	0.0809	0.1438	A7c	Governance	0.0035	0.5102
	DIGI	23.7131	0.0520		DIGI	-0.1311	0.8606
	r-squared	0.3633			r-squared	0.2086	
A4d	Controversies	0.1100	0.0005	A7d	Controversies	0.0091	0.0177
	DIGI	31.5201	0.0002		DIGI	0.4222	0.4122
	r-squared	0.4133			r-squared	0.2739	

that there is a relationship between controversies and ROE.

Digitalization is only positive and significant for the models including the overall ESG score or the controversies score, in both cases using ROE as the dependent variable. In most cases digitalization is insignificant and in some cases, the coefficient is even negative. We see again evidence for the profitability paradox. Hence, we cannot accept the second hypothesis for most cases. There is no strong evidence that digitalization has a positive and significant correlation with profitability in the presence of ESG.

4.3 Is ESG a moderator?

To test whether ESG components have a moderating effect, the interaction parameter of the digitalization and the corresponding ESG metric were included in the models $A5$ and $A8$. The shortened output can be found in table 9 and the extended version in table 13.

Table 9: Regression Coefficients ESG Metrics with Interaction.

		ROE				ROA	
		b	p-value			b	p-value
A5	ESG	0.1266	0.0482	A8	ESG	0.0070	0.2717
	DIGIESG	5.1419	0.0021		DIGIESG	0.2738	0.0517
	DIGI	-324.1847	0.0043		DIGI	-18.6818	0.0510
	r-squared	0.4277			r-squared	0.2399	
A5a	Environment	0.0525	0.5939	A8a	Environment	-0.0035	0.7739
	DIGIE	-2.6667	0.5898		DIGIE	-0.1979	0.5168
	DIGI	230.9236	0.5495		DIGI	15.8005	0.5107
	r-squared	0.3539			r-squared	0.2115	
A5b	Social	0.1175	0.2162	A8b	Social	0.0045	0.6700
	DIGIS	-3.6862	0.1899		DIGIS	-0.2590	0.1034
	DIGI	261.4944	0.1396		DIGI	16.6352	0.1002
	r-squared	0.3754			r-squared	0.2181	
A5c	Governance	0.0768	0.1618	A8c	Governance	0.0032	0.5477
	DIGIG	0.9139	0.6057		DIGIG	0.0662	0.5402
	DIGI	-42.9104	0.7444		DIGI	-4.9596	0.5357
	r-squared	0.3644			r-squared		
A5d	Controversies	0.0840	0.0111	A8d	Controversies	0.0079	0.0476
	DIGIC	1.7434	0.0000		DIGIC	0.0792	0.0107
	DIGI	-135.6982	0.0005		DIGI	-7.1706	0.0153
	r-squared	0.4382			r-squared	0.2816	

A crucial finding of this paper is the effect of the controversy score, as well as its interaction score when compared to taking solely the ESG score or its three main components. In contrast to the other sustainability scores, the controversy score and its interaction with digitalization are significant in all our regressions. For the models *A5d* and *A8d* the regression output shows that the digitalization coefficient is now negative, indicating a negative relationship with profitability while the interaction term and the controversy score have positive and significant coefficients.

This gives reason to conclude that reputation has a substantial impact on profit efficiency regarding banks' digitalization efforts. This finding is also in line with the literature, where trust and the reputation of banks are identified as important factors for the success of digitalization efforts. Forcadell argues that reputation enhances trust, which is a crucial factor when closing branches and merging customers to a less personal approach to banking. (Forcadell et al., 2020).

Hence, we accept the third hypothesis for the controversies score. The controversies score has a moderating effect on the relationship. This implies that reducing controversies may help banks to benefit from their digitalization efforts that otherwise would have no significant relationship with profitability.

Table 10: Regression Coefficients A3-A8.

	ROE ESG Data					
	A3		A4		A5	
	b	p-value	b	p-value	b	p-value
const	2.5495	0.9137	-0.2399	0.9894	-3.1256	0.8641
CreditRisk	-30.3806	0.0000	-26.9078	0.0000	-26.8540	0.0000
Size	-0.2684	0.7437	-0.5423	0.4232	-0.2514	0.7037
CAR1	0.8104	0.0047	0.7913	0.0048	0.6318	0.0277
Year.2015	1.6463	0.4876	1.4970	0.5168	1.4685	0.5286
Year.2016	0.3959	0.8893	0.1421	0.9588	0.0683	0.9807
Year.2017	0.2098	0.9491	-0.6492	0.8333	-0.5404	0.8633
Year.2018	2.6974	0.2680	2.2801	0.2569	2.2898	0.2914
Year.2019	0.0864	0.9763	-0.0159	0.9951	0.9916	0.6858
Year.2020	-2.6381	0.4622	-3.1267	0.3794	-2.8506	0.4285
Year.2021	NA	NA	NA	NA	NA	NA
DIGI	26.0462	0.0234	24.1481	0.0223	-324.1847	0.0043
ESG			0.1688	0.0062	0.1266	0.0482
DIGIESG					5.1419	0.0021
r-squared	34.37%		40.28%		42.77%	

	ROA ESG Data					
	A6		A7		A8	
	b	p-value	b	p-value	b	p-value
const	0.4645	0.8285	0.3121	0.8728	0.1584	0.9363
CreditRisk	-2.1699	0.0000	-1.9801	0.0000	-1.9772	0.0000
Size	-0.0169	0.8193	-0.0319	0.6563	-0.0164	0.8262
CAR1	0.0299	0.1661	0.0289	0.1862	0.0204	0.3474
Year.2015	0.0621	0.7134	0.0540	0.7441	0.0525	0.7537
Year.2016	0.0755	0.6873	0.0616	0.7361	0.0577	0.7576
Year.2017	0.0566	0.8238	0.0097	0.9689	0.0155	0.9511
Year.2018	0.2296	0.2128	0.2068	0.2067	0.2073	0.2275
Year.2019	0.1129	0.5975	0.1073	0.5860	0.1610	0.4151
Year.2020	0.0689	0.8567	0.0422	0.9143	0.0569	0.8863
Year.2021	NA	NA	NA	NA	NA	NA
DIGI	-0.0301	0.9664	-0.1338	0.8387	-18.6818	0.0510
ESG			0.0092	0.1033	0.0070	0.2717
DIGIESG					0.2738	0.0517
r-squared	20.31%		22.94%		23.99%	

4.4 Testing the Model

After analyzing the coefficients and the overall goodness of fit of our model, several tests were conducted. All the following tests are conducted on regression $A5d$, hence taking into account both the controversy score and its interaction with digitalization.

As the first step, we analyze the residual errors for normality. By creating a Q-Q plot, we can get a visual representation of the normality of errors by plotting them against quantiles of distribution (figure 3). Zooming in on the shape of the plotted errors on the Q-Q plot gives the first impression of slightly over-dispersed residuals (figure 4). Our residuals seem to have what is generally described as 'fat tails', which can further be observed on the histogram of residual errors showing a leptokurtic distribution (figure 5), while also showing signs of negative skewness. A positive kurtosis of 5.98 further confirms this intuition. Generally, a kurtosis above 3 could have implications on the t-statistics, however, we can still observe significant parameters and hence do not judge this as a major issue for the stability of our model. The skewness is -0.66, which is proving the fact that the residuals in our model are not normally distributed.

As the last step of analyzing the residuals, we look at some correlations. We start by looking at a graph plotting the residuals and the dependent variable. It can be observed that there seems to be a positive trend and as consequence, we have a strong suspicion of encountering a positive correlation between the two variables (figure 7). A Pearson test confirmed the intuition with a positive correlation of 75% and a p-value significantly below 0.05. The previously obtained non-normality of the distribution of errors questions the exactness of the obtained p-value from the Pearson test. However, the high correlation coefficient of 75% combined with the evidence from the graph (figure 7) let us conclude that the model is missing some variables explaining this correlation.

Taking a look at graph (figure 8), we observe that only the first lag is outside the confidence interval. The following lags show strong evidence that there is no autocorrelation in our model.

Table 11: Pearson´s Correlation Coefficient - Base regression.

Pearson's Correlation Coefficient :	0.749563
Pearson's p-value:	< 0.0000001

4.5 Limitations

This study is subject to several limitations. The first major limitation is the reduced sample size due to limited access to data. The panel data is unbalanced and for several countries, the number of observations is extremely limited, which did not allow us to control for country-specific impacts. Moreover, ESG as a relatively new topic comes with a limited amount of historical data.

Secondly, this study only focuses on listed banks and excludes all non-listed banks, so it is not possible to generalize our findings to those banks. Including non-listed banks could potentially lead to bigger sample size, but might also come with the caveat of more missing data.

As a third limitation, we identified the fact that there is not a unified, global methodology for calculating ESG scores between data providers. This is proved by the fact that some companies receive different ESG scores from different data providers, hence leading to results differing from the ones obtained in this paper.

As the last limitation, we did not have the resources to access internal data for this study, nor could we use any qualitative data. By accessing information regarding IT spending or specific investments, the study could have profited from more granularity. Especially trust and reputation could only be approximated by the available ESG data from Refinitiv.

Chapter 5

Conclusion

The first objective of this report was to determine if the relationship between digitalization and banking profitability is significant and positive in recent years in the Eurozone. A second objective was to determine whether CS behaves as a moderator.

5.1 Discussion

We conclude that digitalization does not necessarily have a positive relationship with profitability, signaling the presence of the profitability paradox as mentioned by the literature. This observation changes little when including the used measures of CS.

Moreover, we conclude that contrarily to other ESG variables used in this study, controversy is significant in all our regressions, indicating the special importance of this factor. Including the interaction of controversies and digitalization in the model confirms the moderating effect of controversies on the success of a bank's digitalization efforts. Other ESG indicators failed to show consistent significance.

Our results confirm and extend the existing findings in the literature. Digitalization efforts of banks have a positive relationship with profitability if the bank simultaneously has few controversies. Fewer controversies might lead to an improvement in trust which can compensate for the increased information asymmetries on the side of the customers caused by digitalization.

5.2 Final Considerations and Further Research

Finally, there are a few considerations for further research that should be highlighted.

Using a cost-efficiency frontier to derive a proxy for digitalization is a less common method. Further research could investigate the differences between this method and more traditional measures. A meta-analysis of digitalization could provide insight into what method most accurately captures the real level of digitalization in banks.

While not the focus of this research, it would be interesting to further research the effect of digitalization with the CS moderator for resistance to crises. For example, looking at the profitability of banks with different levels of digitalization and CS during the Covid-19 pandemic could provide information about the ability of digitalization and reputation to increase profit stability. Furthermore, in a few years, it could be analyzed whether the Covid-19 pandemic had long-term effects on the digitalization strategies of banks.

Moreover, examining the impact of controversies on trust and on the reputation of banks could help to understand whether the controversies score is the most accurate measurement of these variables. Alternatively, customer trust could be measured through qualitative data. For instance, customer interviews could give detailed information about the customers' perception of their banks' activities.

Further research could also follow up on the results of this research by studying the impact of controversies on other performance measures. Ultimately, trying to prove causality would be of the highest interest as it could help to develop advice for banks' digitalization strategies.

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Appendix A

Appendix

Table 12: All Regression Coefficients ESG Metrics.

ROE	A4		A4a		A4b		A4c		A4d	
	b	p-value	b	p-value	b	p-value	b	p-value	b	p-value
const	-0.2399	0.9894	12.9866	0.6984	13.8195	0.5849	7.3062	0.7453	-49.0531	0.0973
Interaction2	24.1481	0.0223	21.8487	0.0987	22.8914	0.0734	23.7131	0.0520	31.5201	0.0002
CreditRisk	-26.9078	0.0000	-30.0512	0.0000	-30.5697	0.0000	-27.6482	0.0000	-28.1134	0.0000
Size	-0.5423	0.4232	-0.8173	0.5751	-0.9432	0.3701	-0.6529	0.4565	1.3470	0.1620
CAR1	0.7913	0.0048	0.8199	0.0014	0.8393	0.0036	0.8039	0.0051	0.8150	0.0059
ESG	0.1688	0.0062								
Year.2015	1.4970	0.5168	1.5837	0.5040	1.3920	0.5384	1.8476	0.4454	1.2861	0.5657
Year.2016	0.1421	0.9588	0.3625	0.8992	0.2147	0.9397	0.4316	0.8776	0.2851	0.9159
Year.2017	-0.6492	0.8333	0.5898	0.8645	-0.8236	0.7880	0.0352	0.9909	0.2689	0.9341
Year.2018	2.2801	0.2569	3.0377	0.2205	1.7552	0.4293	2.4155	0.2861	4.2009	0.0501
Year.2019	-0.0159	0.9951	0.2979	0.9185	-1.2646	0.6364	-0.3191	0.9056	2.5723	0.3853
Year.2020	-3.1267	0.3794	-2.4013	0.4886	-3.8628	0.3307	-3.0618	0.3990	-1.2393	0.7285
Environment			0.0498	0.6146						
Social					0.0966	0.3103				
Governance							0.0809	0.1438		
Controversies									0.1100	0.0005

ROA	A7		A7a		A7b		A7c		A7d	
	b	p-value	b	p-value	b	p-value	b	p-value	b	p-value
const	0.3121	0.8728	-0.3143	0.9368	0.8181	0.7712	0.6706	0.7668	-3.7992	0.2769
Interaction2	-0.1338	0.8387	0.2832	0.8060	-0.1291	0.8699	-0.1311	0.8606	0.4222	0.4122
CreditRisk	-1.9801	0.0000	-2.1945	0.0000	-2.1758	0.0000	-2.0515	0.0000	-1.9826	0.0001
Size	-0.0319	0.6563	0.0240	0.8921	-0.0381	0.7535	-0.0336	0.7017	0.1165	0.3077
CAR1	0.0289	0.1862	0.0292	0.1952	0.0308	0.1376	0.0296	0.1748	0.0303	0.1874
ESG	0.0092	0.1033								
Year.2015	0.0540	0.7441	0.0668	0.7024	0.0541	0.7496	0.0709	0.6784	0.0324	0.8379
Year.2016	0.0616	0.7361	0.0780	0.6812	0.0698	0.7113	0.0770	0.6766	0.0663	0.7131
Year.2017	0.0097	0.9689	0.0283	0.9167	0.0242	0.9280	0.0491	0.8438	0.0615	0.8078
Year.2018	0.2068	0.2067	0.2042	0.2977	0.2000	0.3329	0.2174	0.2208	0.3538	0.0496
Year.2019	0.1073	0.5860	0.0971	0.6625	0.0705	0.7753	0.0953	0.6441	0.3183	0.1931
Year.2020	0.0422	0.9143	0.0513	0.8799	0.0305	0.9488	0.0506	0.8996	0.1845	0.6443
Environment			-0.0037	0.7627						
Social					0.0030	0.7754				
Governance							0.0035	0.5102		
Controversies									0.0091	0.0177

Note: Empty cells result from the variable not being included in the model.

Table 13: All Regression Coefficients ESG Metrics with Interaction.

ROE	A5		A5a		A5b		A5c		A5d	
	b	p-value	b	p-value	b	p-value	b	p-value	b	p-value
const	-3.1256	0.8641	10.1652	0.7626	9.5657	0.6980	7.6886	0.7360	-46.3261	0.1288
Interaction2	-324.1847	0.0043	230.9236	0.5495	261.4944	0.1396	-42.9104	0.7444	-135.6982	0.0005
CreditRisk	-26.8540	0.0000	-29.7391	0.0000	-30.6704	0.0000	-27.8114	0.0000	-27.7893	0.0000
Size	-0.2514	0.7037	-0.7150	0.6228	-0.8902	0.3947	-0.6502	0.4605	1.3413	0.1729
CAR1	0.6318	0.0277	0.8214	0.0016	0.9916	0.0031	0.7905	0.0069	0.8122	0.0085
ESG	0.1266	0.0482								
Year.2015	1.4685	0.5286	1.5407	0.5222	1.1705	0.6067	1.8744	0.4445	1.1347	0.6141
Year.2016	0.0683	0.9807	0.2525	0.9303	-0.2271	0.9366	0.4316	0.8784	-0.0999	0.9708
Year.2017	-0.5404	0.8633	0.4836	0.8875	-1.9545	0.5555	-0.0047	0.9988	-0.3665	0.9134
Year.2018	2.2898	0.2914	2.8596	0.2561	1.4474	0.5213	2.5781	0.2561	3.3901	0.1446
Year.2019	0.9916	0.6858	0.2356	0.9362	-1.2048	0.6404	-0.2343	0.9298	3.0389	0.2955
Year.2020	-2.8506	0.4285	-2.3487	0.4979	-4.1737	0.2923	-3.1220	0.3941	-1.3702	0.7011
Environment			0.0525	0.5939						
Social					0.1175	0.2162				
Governance							0.0768	0.1618		
Controversies									0.0840	0.0111
DIGIESG	5.1419	0.0021								
DIGIE			-2.6667	0.5898						
DIGIS					-3.6862	0.1899				
DIGIG							0.9139	0.6057		
DIGIC									1.7434	0.0000

ROA	A8		A8a		A8b		A8c		A8d	
	b	p-value	b	p-value	b	p-value	b	p-value	b	p-value
const	0.1584	0.9363	-0.5237	0.8966	0.5193	0.8546	0.6983	0.7595	-3.6754	0.2974
Interaction2	-18.6818	0.0510	15.8005	0.5107	16.6352	0.1002	-4.9596	0.5357	-7.1706	0.0153
CreditRisk	-1.9772	0.0000	-2.1713	0.0000	-2.1829	0.0000	-2.0633	0.0000	-1.9679	0.0001
Size	-0.0164	0.8262	0.0316	0.8599	-0.0344	0.7774	-0.0334	0.7046	0.1163	0.3117
CAR1	0.0204	0.3474	0.0293	0.2004	0.0415	0.0861	0.0287	0.1959	0.0302	0.1950
ESG	0.0070	0.2717								
Year.2015	0.0525	0.7537	0.0636	0.7194	0.0386	0.8197	0.0728	0.6735	0.0255	0.8728
Year.2016	0.0577	0.7576	0.0698	0.7162	0.0388	0.8369	0.0770	0.6788	0.0489	0.7877
Year.2017	0.0155	0.9511	0.0204	0.9397	-0.0552	0.8425	0.0462	0.8548	0.0327	0.8992
Year.2018	0.2073	0.2275	0.1910	0.3366	0.1784	0.3875	0.2292	0.2005	0.3170	0.0903
Year.2019	0.1610	0.4151	0.0925	0.6801	0.0747	0.7572	0.1015	0.6208	0.3395	0.1616
Year.2020	0.0569	0.8863	0.0552	0.8709	0.0087	0.9854	0.0462	0.9087	0.1786	0.6560
Environment			-0.0035	0.7739						
Social					0.0045	0.6700				
Governance							0.0032	0.5477		
Controversies									0.0079	0.0476
DIGIESG	0.2738	0.0517								
DIGIE			-0.1979	0.5168						
DIGIS					-0.2590	0.1034				
DIGIG							0.0662	0.5402		
DIGIC									0.0792	0.0107

Note: Empty cells result from the variable not being included in the model.

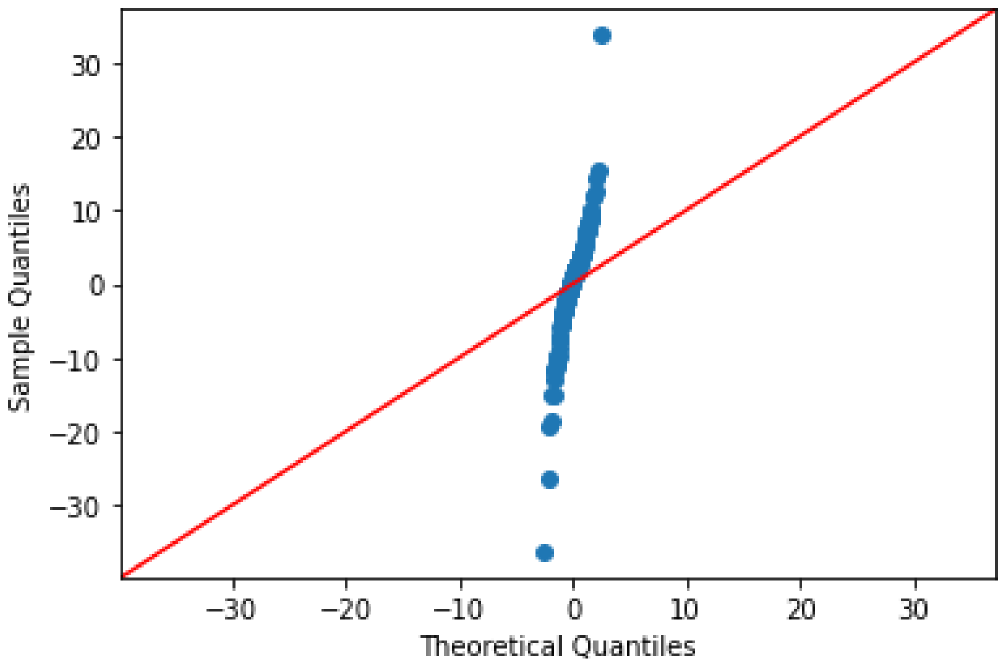

Figure 3: Q-Q Plot of Regression A5d.

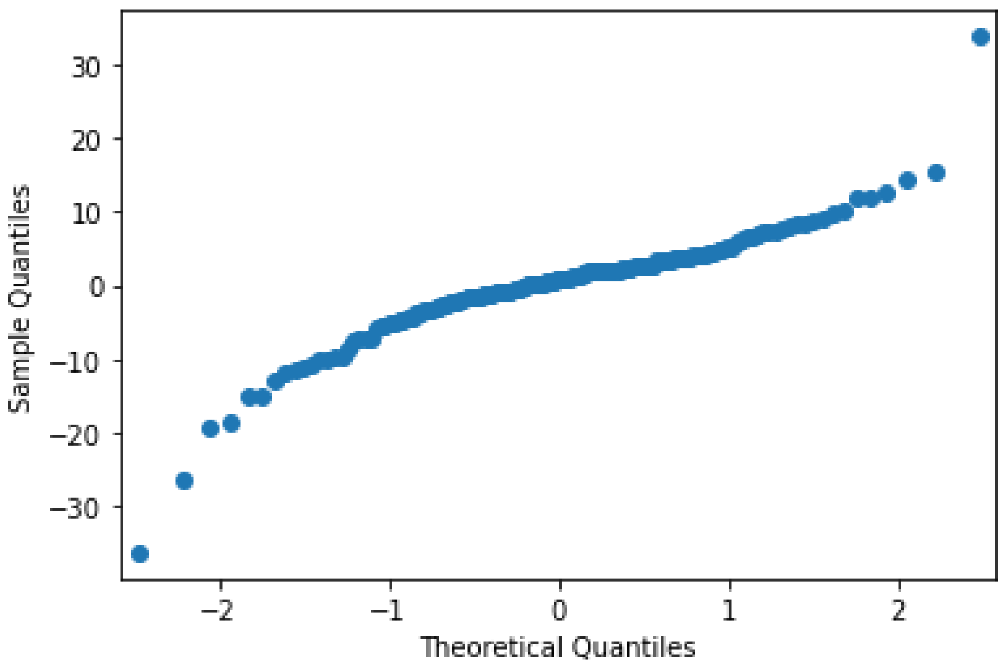

Figure 4: Q-Q Plot of Regression A5d - close-up.

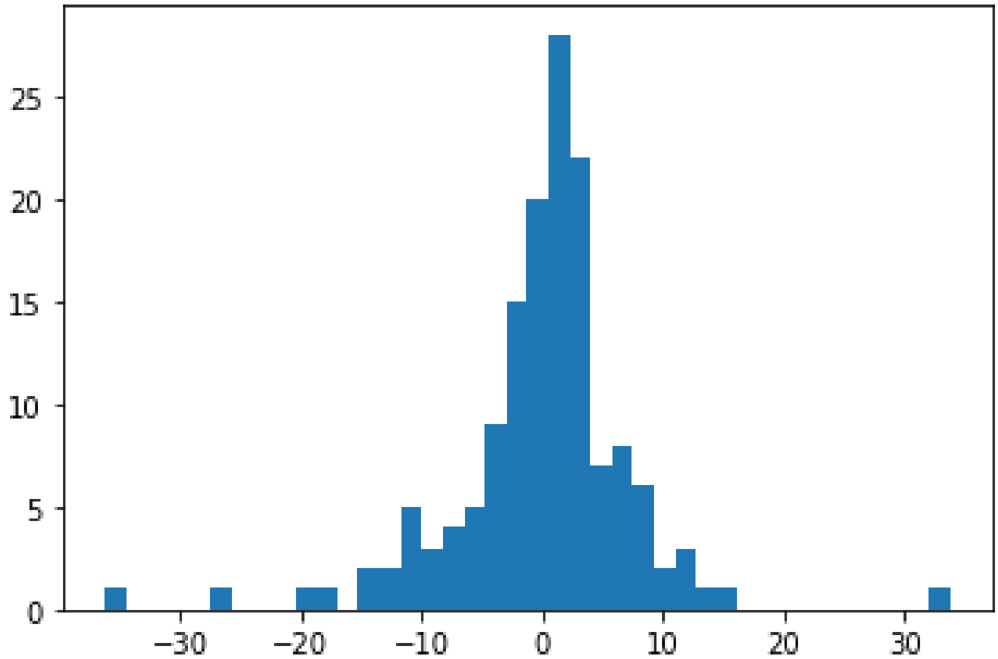

Figure 5: Histogram of Residuals from Regression A5d.

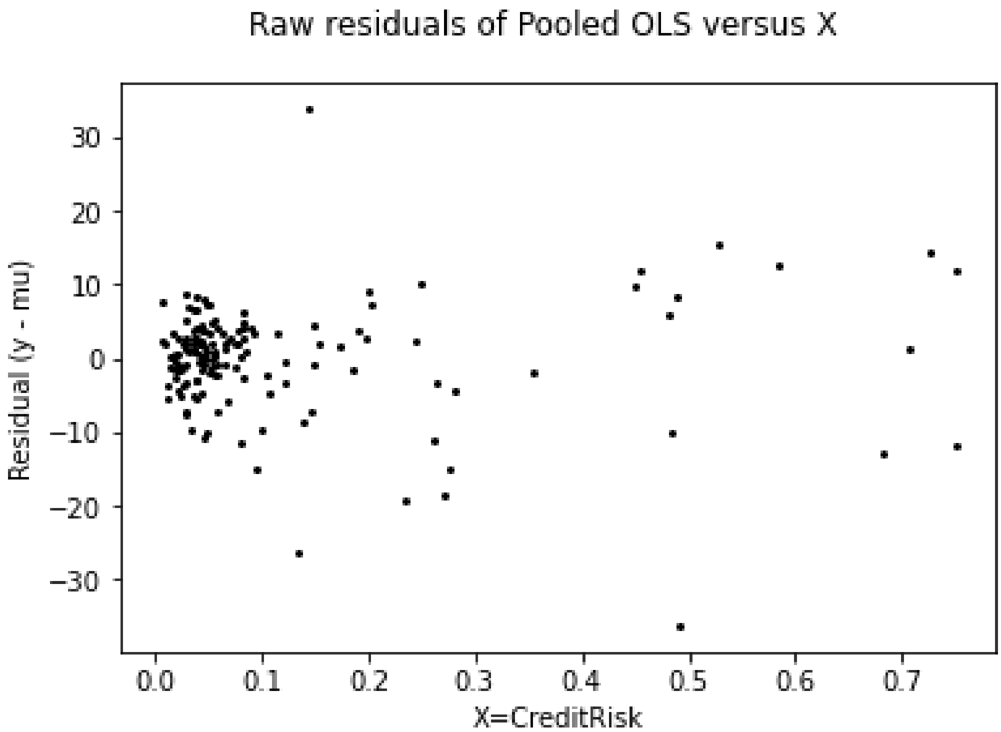

Figure 6: Residuals of Pooled OLS regressed on Interaction Variable for Regression A5d.

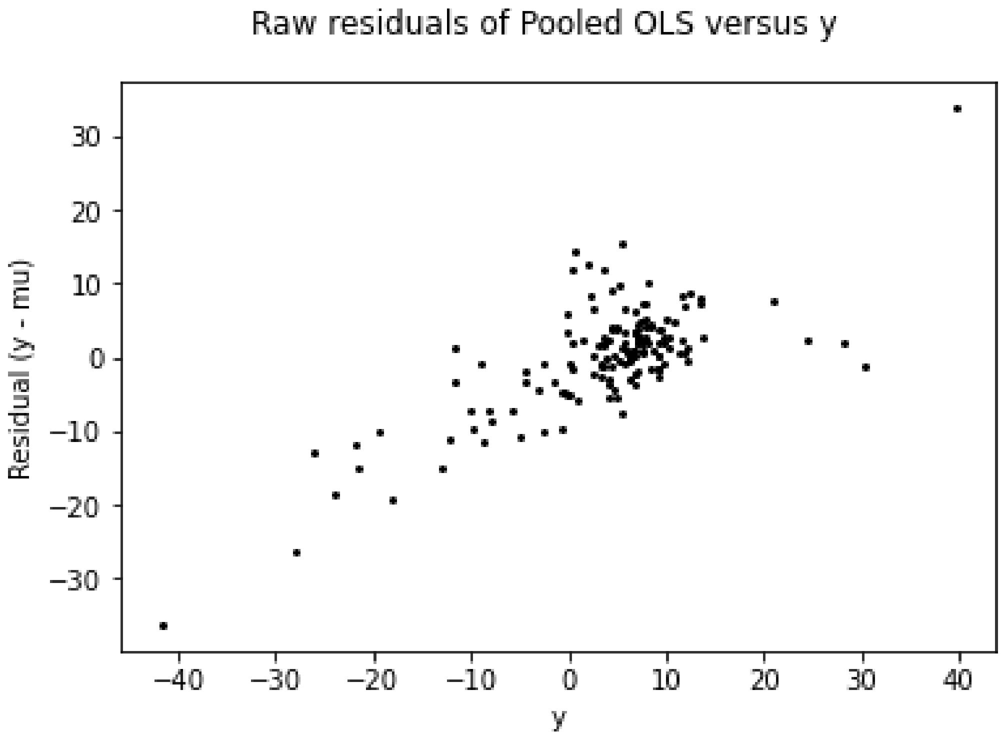

Figure 7: Regiduals regressed on dependent variable (ROE) for Regression A5d.

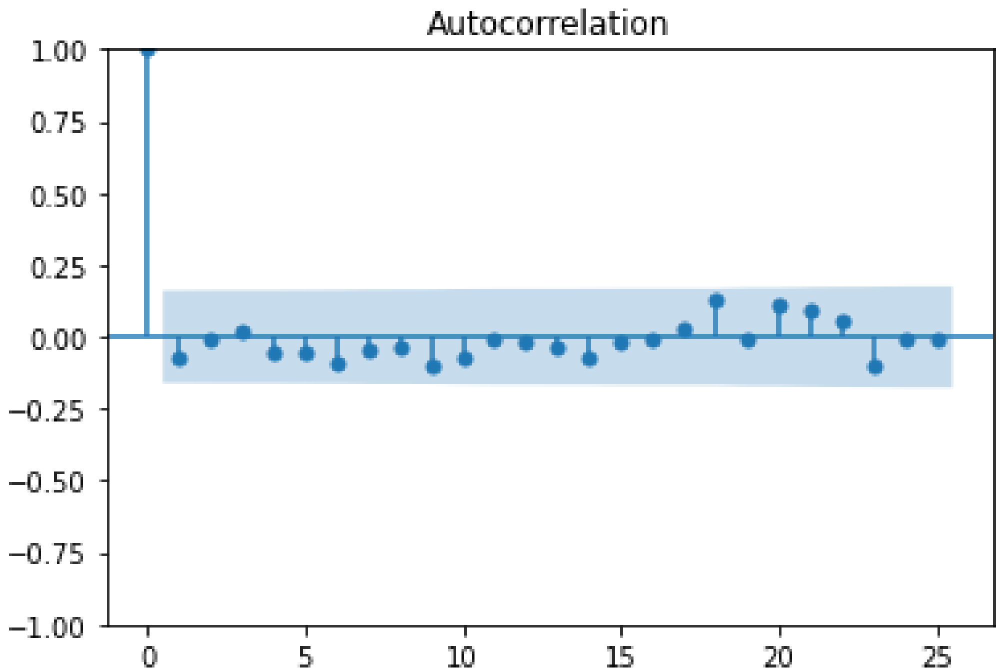

Figure 8: ACF of Regression A5d.