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The effects of digitalisation of European banks on the credit market

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Abstract

The world of banking will not stay the same during our lifetime. Digital products are already implemented in other industries, however the banking industry seems to be subordinated. The competition in the financial sector is increasing over the last decade, and if the banks don't follow this digital revolution they might become redundant. The so-called Fintech companies are taking over market share in the financial industry by offering identical products but, compared to banks, through a digital platform only. This development will change the way money is being transferred from borrower to lender. Traditional banks have started offering digital financial services through online website and mobile phone applications the last years, yet these effects are still opaque. This study investigates the effects of digitalisation of European banks on their credit provision and how these digital financial services affected their total loans and non-performing loans (NPL). The data consists of 116 European banks divided over 20 countries from the period 1993-2018, which covers the first steps of the implementation of digital financial services. The results show that the gradual implementation of digital services increase the total loans and NPL of European banks, but deteriorates the bank's credit provisioning.

Keywords: Automation, Digitalisation, European Banks, Credit, Loans, NPL

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1. Introduction

The financial platforms of the future are not going to be the traditional banks but the technology firms" - Henri Arslanian, Tedx 2016

With the introduction of the Payment Services Directive (PSD2) in the beginning of 2018, banks have been challenged to embrace the digital transformation. The main objective for this new European regulation is to encourage competition in the financial market, as well as increasing the transparency and security of payment services (Cortet *et al*., 2017). Likewise, the increasing competition in the financial market will result in more choices for banking customers. The demand for digital financial services, especially among the younger population, is increasing and can make the use of payment and other financial services by traditional banks redundant. However, European banks have gradually implemented new technologies in their business model, such as mobile phone applications and online banking. Nevertheless, online platforms other than banks are now offering similar products and are yet gaining market share. As a matter of fact, the number of banks has decreased since the digitalisation of financial services (Alt *et al*., 2018). The digital transformation has a substantial influence on the financial sector. The increasing availability of financial services and financial inclusion has changed consumer behavior towards online banking (Pousttchi & Dehnert, 2018). However, the increase of financial inclusion enables the 'access' to credit for the poorest (people in lowest income quintiles) which could have its challenges (Bernards, 2019; Claessens *et al*, 2018). These challenges include ensuring consumer and investor protection which is equivalent in this study to the borrower and lender of credit.

According to a Financial Times article by Olanrewaju (2013), ..."retail banks have digitized only 20 to 40 percent of their processes; 90 percent of European banks invest less than 0.5 percent of their total spending on digital" (Alt *et al*., 2018). Traditional banks tend to be overdue when it comes to adapting to these new digital developments, which gives the opportunity for alternative suppliers of financial services, such as online platforms, to attract consumers that are inclined or willing to try these new digital financial services. Moreover, the global investment in online platforms tripled to roughly $12 billion in 2014, showing that there is a digital revolution (Dickerson *et al*., 2015).

The increasing digital financial services will benefit consumers from a user's experience and also from a convenience perspective. The financial industry is continuously transforming how financial services are being delivered and will give access to more people around the world. The increasing opportunities for online platforms as alternatives for traditional banks could also have its downsides. Online banking offered by these alternative online platforms is vulnerable to new credit risks, since the accessability to the credit market becomes greater (Arner *et al*., 2016). However, in the study by Arner *et al*. (2016) these risks are outweighted by the benefits, since online platforms have better-organized data which allows these platforms to offer products that are better aligned to consumers' risk profile. The use of better-organized data by means of new digital technologies promise better credit risk assessments (Claessens *et al*., 2018).[1] The major difference between banks and these new online platforms is that "banks are subject to various prudential regulations and supervision, including extensive data reporting requirements" (Claessens *et al*, 2018, p.31). The online platforms do not yet need to adhere to this prudential regulations and are therefore seen as the banks' main competitor in providing credit to borrowers.

By giving insights in the effects of the new digital financial services offered by banks to their customers it would help to comprehend the digital revolution. Therefore, this research will perform an event study in which the focus will be on European traditional banks and the effects of their implementation of new digital financial services, such as mobile phone applications and online banking, as well as the automation processes within banks. The credit provision offered by the traditional banks before and during their implementation of the digitalisation of their financial services will be included in this research as well as how different steps of the digitalisation changed the total loans and the non-performing-loans (NPL) of these banks. Because the rise of digital financial services has only recently developed, not much is known about the impact for banks and the overall financial market. Therefore, it is becoming an interesting and therewith a growing research area (Li *et al*., 2017). Previous research has primarily focused on the stand-alone performance of online platforms (Berkovich, 2011; Li *et al*., 2017; Nakashima, 2018) or made a theoretical contribution on the digital transformation of financial services (Gomber *et al*., 2017; Magnuson, 2018; Navaretti *et al*., 2018; Schindler, 2017; Zetsche *et al*., 2017). This study bridges the gap between the

[1] Claessens *et al*. (2018) promise also greater convencience and lower transaction costs with the use of new digital technologies.

current literature on these new financial services and the (up to now) empirical contributions, to see whether an increase in total loans and non-performing loans goes hand in hand with the initiation of automation and digitalisation processes by European banks. It is also one of the first studies to examine the effect of automation and digitalisation using quantitative methods. Altogether, this led to the following research question:

What are the effects of the implementation of new digital financial services of European banks on the credit market?

One could argue that the rise of alternative online platforms emerged after the global financial crisis of 2008. This crisis deteriorated the public perception of the traditional banks (Arner *et al*, 2016). It also had regulatory and competitive consequences for banks, which has increased banks' compliance obligations. Another important note from the study by Arner *et al*. (2016) is that these reforms for banks after the financial crisis had the unintended consequence of given leeway for these new technological firms. Nevertheless, this should not directly cause a shift in demand for banking customers. Before the crisis started, many people had their savings account at their nearest bank or the bank they trusted in. It could be argued that traditional bank-lending markets have less information asymmetry compared to these new online patforms, since traditional banks "can use collateral, certified accounts and regular reporting to obtain information on the borrower's credibility" (Emekter *et al*., 2015, p.55), whereas for online platforms this information is often missing. This information asymmetry can result in both adverse selection and moral hazard problems (Akerlof, 1970). The concept of information asymmetry is well-known in the financial literacy, and within this context it relates to the concept of providing liquidity by lenders to borrowers. Adverse selection would mean that (ex ante) only low-quality borrowers apply for a loan, whereas moral hazard means that it would change the behaviour of the borrower (ex post) and increase the credit risk. If lenders, in this case traditional European banks, are aware of the quality of the borrowers, they can change the interest rate on the principal amount that is borrowed. However, this process for banks to gather information of their clients is time consuming and costly. On the other hand, online platform lenders use financial technologies to automate processes to determine borrower's identity or credit risk (Treasury U.S., 2016). The matching between lenders and borrowers by online platforms is provided at a lower cost compared to what these traditional banks can offer (Nicoletti, 2017). Big data and selflearning algorithms are more cost-effectively and reliable than the models of traditional banks to estimate credit risks (Dorfleitner *et al*., 2018). However, if all online platform lenders are being competititive, it would mean that they can attract and retain borrowers and investors, which will lower the transaction costs and enhance the risk assessment through reduced information asymmetries (Financial Stability Board, 2017).

The increasing demand for digital financial services comes together with higher levels of regulation, including the PSD2. These regulations should enhance the financial sector stability as well customer protection (Kotarba, 2016). Besides the better accessibility for customers towards banking credit, it also brings challenges for the traditional banks as well as for financial regulators (Forest & Rose, 2015). For instance, the Dutch authority for the financial markets (AFM), is committed to transparent financial markets but at the same time protecting this transparency (AFM, 2019). In their survey of the trends and risks on the financial markets, they highlight the important aspects of the digitalisation of the financial sector. One of the biggest implications of the digitalisation for these regulators is the increasing usage of data and technology (AFM, 2019). The current problem, as mentioned earlier, is that the new online platforms are not subject to financial supervision which makes it for monitoring authorities such as the AFM more difficult to oversee and control the financial markets. Therefore, the overall impact of the digitalisation on financial services is yet to be discovered. Not only from a consumer perspective, but also from the banking– and financial authorities perspective. This research contributes to enriching the literature on the effects of digitalisation from the banking perspective.

The paper is organized as follows. First, an overview of existing literature is given concerning the development of the financial market in the last two decades. Second, three hypotheses with additional theory are discussed. Third, the study design, in which will be elaborated on the choice for European banks as the main data and the use of an event study to test the hypotheses is described. Fourth, the results are showed. And last, the conclusion which includes on the answer on the research question is described.

2. Theory and hypotheses

This study will focus on the credit provision offered by European banks before and during their implementation of new digital financial services. Here, also a distinction between two types of digital services is made, namely the automation processes and digitalisation processes by banks. It can be argued that both types of digital services intertwine, yet the major difference between the two is that automation has no direct influence for banking customers, but is concerned with internal developments within banks and limited to the bank's efficiency. On the other hand, digitalisation is the process initiated by banks to ease the accessibility for banking customers. The increasing accessibility through means of the digitalisation of financial services could enhance the credit provision by European banks. Altogether, one could say that automation has implications for the internal operations for banks, whereas digitalisation embraces these internal developments and exploits it to the general public.

The effect of the financial crisis has had an impact on the emergence of these new digital financial services, meaning that from 2008 onwards traditional banks reinvented their business models and started to provide better aligned customer experience by introducing digital services, such as online banking and mobile phone applications. From that moment on, banks started working on increasing efficiency by means of digitalisation (Vasiljeva & Lukanova, 2016). In their study, Vasiljeva & Lukanova (2016) developed a conceptual framework that highlights the determinants of the digitalisation process of traditional banks, which are e.g. new payment infrastructure and analysis of big data.

To practically examine the effects of digitalisation of traditional banks on the credit market, three hypotheses are developed grounded with theoretical back up. A panel regression will be executed, where the dependent variable will be the credit provision (*CreditP)* of traditional banks. The independent variables will consist of two major components of the credit provision, which are total loans (*Total_Loans*) and non-performing-loans (*NPL*). The databases that will be used are discussed in the next section, as well as the retrieval of the abovementioned variables and the selection of the model.

Based on the discussion above, three hypotheses are developed to test the effects of the digitalisation of traditional banks on the credit market. The first hypothesis that will be tested is to see whether these new financial technologies did in fact lead to higher credit issuing by banks and therefore resulted in easier access for borrowers to apply for a loan.

> ***Hypothesis 1:*** *New digital financial services implemented by traditional banks increase the credit issuing by banks to customers.*

Second, the easier access to credit could also mean that low-quality borrowers are eligible for a loan, which can give a higher chance of default by these type of borrowers. In the study by Makri *et al*. (2014) they showed that lower quality of borrowers, e.g., lack of employment, increase the likelihood of default.

> ***Hypothesis 2:*** *Improved access to banking credit to customers by means of digitalisation increases the chances of default.*

At last, the banks will despite the higher chances of default still earn a profit, because the higher credit issuing outweighs the loss on non-performing loans. Otherwise, the credit standards set by the banks are too low. The higher credit rates as a whole give banks a higher revenue. Therefore, the last hypothesis is:

> ***Hypothesis 3:*** *Traditional banks using new digital financial services earn positive returns on their credit provision despite the higher default rates.*

On the basis of these three hypotheses default rates can be tested and compared, based on non-performing-loans (NPL) and credit issuing for European banks before and during their implementation of these new digital financial technologies. The results will give an useful insight in the effectiveness of the digitalisation of the banking industry, and give recommendations for future studies in this direction. In the next section the methodology behind these hypotheses will be discussed, accompanied with the respective variables and the selection of the models.

3. Study design

This chapter covers the methodology of the study. Starting with section 3.1, in which the data selection will be described together with the sample and criteria. Section 3.2 outlines the dependent variable, whereas section 3.3 and 3.4 outlines the independent variables and control variables, respectively. At last, section 3.5 handles the model selection.

3.1 Data sample description

The data will be used on the credit volume as well as the credit default rates of traditional European banks and will be retrieved from the databases of BankFocus (Orbis) and Thomson ONE (Eikon). The former retrieves the list of European banks, after selecting for status (active company), specialization (commercial bank), world region (Europe) and whether it is (or was) publicly listed. The latter database is used to retrieve data on total loans and non-performing-loans from the list of traditional European banks. The reason why this study includes only European banks and excludes non-European banks (e.g., US banks) is to take into account the PSD2 regulation, and to elaborate on the results from the study by Makri *et al*. (2014), who investigated the determinants of non-performing loans (default rates) in the Eurozone.

The information on the implementation of digital financial services are available through the banks' annual reports, which is also retrieved from the Eikon database. The observations in the sample cover the period from the period 1993 – 2018, which incorporates the implementation of digital financial services by these European banks, classified in automation and digitalisation. The impact of other digital financial services that are not provided by European banks, but rather by non-financial institutions regarded as Fintech companies are excluded from this analysis, since the overall effect of these competing platforms is yet unknown for the banking industry. Ultimately, the total sample consists of 116 banks distributed over twenty European countries. The list of the European banks included in the sample can be found in table 1 in Appendix A.

Furthermore, to obtain data for the availability of digital financial services by banks, additional literature is used from the European banks'experimental studies from Deloitte and the European Investment Bank (EIB) who gave an overview of the implementation of European banks according to their digitalisation process. In these studies, countries are grouped in different categories based on their digital advancements. An overview of the country's banks and the year they initiated these digital financial services is listed in table 2 in Appendix B. The variables that will be used for the analysis are originated from the databases and annual reports of the included traditional banks, which will be explained in the next sections. Table 3 in Appendix C gives a short description of all the included variables retrieved from the Eikon and Thomson ONE database.

3.2 Dependent variable

The variable *Credit_Provision* is the amount of credit available by banks depending on their total credit capacity deducted by the amount of non-performing-loans (NPL), controlling for GDP and market size. The dependent variable is the outcome of the subtraction of both independent variables, controlling for market size and GDP, which will be explained further on. The credit provision by banks is dependent on the total amount of loans deducted by the non-performing loans, ceteris paribus. Other factors that may influence the credit provision, such as external governance regulations or GDP per capita are excluded from the analysis, as well as other banking activities.

Therefore, the independent variables $Total\_Loans$ and NPL will be handled as a dependent variable in the analysis to test the hypotheses. This is evident because the dependent variable is the outcome of the sum of the independent variables, controlling for market size, GDP, fixed- and interaction effects.

3.3 Independent variables

The independent variable $Total\_Loans$ of banks will be the sum of total outstanding loans to the non-financial sector. These loans are thus meant for the public, e.g., banking customers. Since data for consumer & installment loans was limited available through Eikon, the total loans of European banks is multiplied by the average percentage of consumer& installment loans. The credit default of European banks will be measured on the basis of their non-performing loans (NPL), which is the amount of loans that were defaulted by the borrower. Additionally, every independent variable discussed in this section will be handled as a standalone dependent variable, because this study is interested in the impact of digitalisation on both total loans and non-performing loans.

In this study, the most critical variables are captivated into two dummy variables, which indicates the automation process and the digitalisation process of European banks.

The dummy variable is equal to 1 if European banks implemented either automation or digitalisation, and zero otherwise. This dummy variable is measured on country level, since it would be difficult to compare countries based on their automation and digitalisation process if there are within country differences (e.g. banks within a specific country initiated automation and digitalisation in various years).

3.4 Control variables

In addition, several control variables are included in the model, including GDP (GDP), country, bank and year specific controls, as well as interaction terms. These variables are incorporated to account for the differences of European countries across the years and as a robustness check to the OLS regression models.

The relation between GDP and banks is that it if GDP is decreasing, the economy tends to be in a recession and less people will be incentivized to apply for a loan. Moreover, banking customers that already applied for a loan have more difficulty to fullfill their repayment. Therefore, GDP has a negative effect on non-performing loans, which indicates that in times of recession, NPL tend to increase (Makri *et al.*, 2014). On the contrary, the size and quantity of loans outstanding is positively related to GDP.

Since the representativeness of the countries is unfairly distributed over the sample, and the dataset is considered unbalanced due to inconsistent observations for certain banks during certain years, the study also controls for country fixed effects as well as year fixed effects. Additionally, these fixed effects serve as a proxy for unobservable invariant measurements.

3.5 Models

To approach the research question, the most appropriate model for this study is a panel regression model. The effect of digital financial services (both automation and digitalisation) is tested in multiple ways. First, a model without control variables is performed to analyse the effect of digital financial services on total loans and NPL. Second, the model with GDP, fixed year, fixed country and fixed bank effects is performed with robust standard errors.

For each independent variable $Total\_Loans$ and NPL a multivariate OLS regression is applied. The main panel regression model has the following form, where each European bank is denoted by subscript (i), the countries by subscript (j) and the year dimension by subscript (t):

$$Credit\_Provision_{ijt} = \beta_0 + \beta_1 Total\_Loans_{ijt} + \beta_2 NPL_{ijt} + \beta_3 Automation_{jt} + \beta_4 Digitalisation_{jt} + \beta_5 GDP_{jt} + \beta_6 Fixedyear_{ij} + \beta_7 Fixedcountry_{it} + \beta_8 Fixedbank + \varepsilon_{ijt} \quad \textbf{(1)}$$

β_0 = the constant of the regression model.

$\beta_1 - \beta_8$ = the main independent variables and control variables.

ε_{ijt} = the error term of the regression model, which is expected to be 0.

The model above is split into smaller models for testing the hypotheses. Since there are three hypotheses, each hypothesis has its own model. Additionaly, each hypothesis is performed with and without fixed effects. The interaction effects are discussed in section 4.4, including the other robustness checks.

3.5.1 Hypothesis 1

For the first hypothesis, the dependent variable is $Total\_Loans$. Therefore, the model for hypothesis 1 looks as follows:

$$Total\_Loans_{ijt} = \beta_0 + \beta_1 Automation_{jt} + \beta_2 Digitalisation_{jt} + \varepsilon_{ijt} \quad \textbf{(2)}$$

Below represents the same model with added control variables:

$$Total\_Loans_{ijt} = \beta_0 + \beta_1 Automation_{jt} + \beta_2 Digitalisation_{jt} + \beta_3 GDP_{jt} + \beta_4 Fixedyear + \beta_5 Fixedcountry + \beta_6 Fixedbank + \varepsilon_{ijt} \quad \textbf{(3)}$$

3.5.2 Hypothesis 2

The second hypothesis will look at whether there is an increase in NPL due to these digital financial services, therefore the model will look as follows:

$$NPL_{ijt} = \beta_0 + \beta_1 Automation_{jt} + \beta_2 Digitalisation_{jt} + \varepsilon_{ijt} \quad \textbf{(4)}$$

Below is the same model added with control variables:

$$NPL_{ijt} = \beta_0 + \beta_1 Automation + \beta_2 Digitalisation + \beta_3 GDP_i + \beta_4 Fixedyear + \beta_5 Fixedcountry + \beta_6 Fixedbank + \varepsilon_{ijt} \quad \textbf{(5)}$$

3.5.3 Hypothesis 3

At last, the third hypothesis is handled slightly different. Since this hypothesis looks at the profitability of banks, the logarithm of both total loans and NPL is taken, and the percentage change of both variables is decisive whether the implementation of digital financial services is profitable or not. This means that a higher percentage change in total loans compared to NPL is profitable, whereas a higher percentage change in NPL indicates the opposite.

In simplified terms, the credit provision is the total loans subtracted by the non-performing loans[2].

$$Credit\_Provision_{ijt} = Total\_Loans_{ijt} - NPL_{ijt} \tag{6}$$

$$\Delta\%Total\_Loans_{ijt} = \frac{100 \times (logTotal\_Loans_{ijt}(\_n) - logTotal\_Loans_{ijt}(\_n-1)}{logTotal\_Loans_{ijt}(\_n-1)} \tag{7}$$

$$\Delta\%NPL_{ijt} = \frac{100 \times (logNPL_{ijt}(\_n) - logNPL_{ijt}(\_n-1)}{logNPL_{ijt}(\_n-1)} \tag{8}$$

According to these three models above (6,7,8), if the percentage change in total loans is higher than that of NPL, the credit provision by banks also increases and therefore the bank would become more profitable, due to an increase in rent payments by banking customers. However, a higher increase in NPL compared to total loans would indicate that banks have problems in receiving loan payments by banking customers and therefore have a lower credit provision, ceteris paribus.

Finally, the first two hypotheses uses standardized values for total loans and NPL rather than absolute values, since this will improve the comprehensibility of the regression coefficients. Consequently, the study is better able to explain the increase or decrease for both total loans and NPL when taking into account the implementation of these new digital financial services.

[2] This is a simplified method to calculate credit provision by banks, other factors are excluded.

4. Results

This chapter provides the results of the models discussed in the previous chapter. Starting with section 4.1, which presents the descriptive statistics of the variables. Section 4.2 discusses the correlation matrix between the dependent and independent variables. Section 4.3 highlights the results for each hypothesis, whereas section 4.4 handles the additional robustness checks.

4.1 Descriptive statistics

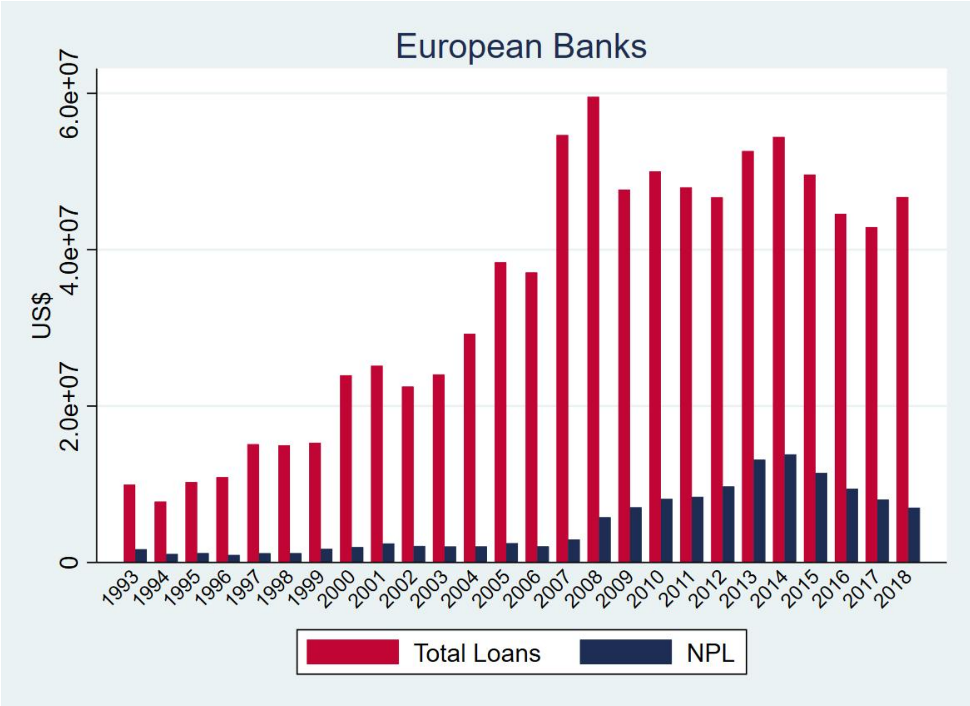
Table 1 presents the descriptive stastistics for the variables for the observations from 1993 to 2018, for a sample of 116 banks divided over 20 countries. As can be seen in the table below, is that more European banks in the sample have implemented automation processes than digitalisation processes. This argument holds in existing literature, considering the fact that banks adopted automation processes before going digital.

Table 1: Summary statistics of variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Credit_Pr~on	1,669	3.19e+07	5.68e+07	-3.25e+07	5.55e+08
Total_Loans	1,669	3.76e+07	6.45e+07	6485.901	5.76e+08
NPL	1,669	5662255	1.28e+07	0	1.16e+08
GDP	1,621	1.06e+12	9.09e+11	1.02e+10	3.95e+12
logCredit_~n	1,630	15.63008	2.247664	8.775843	20.13503
logTotal_L~s	1,669	15.7972	2.223333	8.777386	20.17215
logNPL	1,651	13.22523	2.783066	2.302585	18.57123
logGDP	1,621	27.21313	1.085583	23.04118	29.00413
Automation	1,669	.6920312	.461792	0	1
Digitalisa~n	1,669	.379269	.4853506	0	1

The number of observations drops with 48 when controlling for GDP. Since this is a minor adjustment to the sample size, it should have no major influence on the regression results. The next figure shows the relationship between total loans and non-performing loans for European banks within the time period of 1993 – 2018.

Figure 1: Total loans and non-performing loans (NPL) for European banks in the period 1993-2018



Interestingly, in figure 1 it can be seen that total loans for European banks is increasing in the period before the financial crisis, and that the amount of NPL is increasing in the years thereafter. Additionally, section 4.3. and 4.4 will control for this phenomenon by taking into account the implementation of digital financial services and by doing robustness checks, respectively.

4.2 Correlation matrix

Before the regression models are performed, the correlation matrix is given between all the included variables for the whole sample. Most of these correlation coefficients are below 0.5, indicating that there is no correlation between the independent variables in the sample. Coefficients exceeding the range of 0.7 could indicate multicollinearity. However, in this study the credit provision is the sum of total loans and non-performing loans, in which the latter can be interpreted as a negative value. Therefore, the correlation between credit provision, total loans and non-performing loans is rather high but can be justified. These high correlations between the abovementioned variables is controlled for by means of the variance inflation factor (VIF). The results are presented in Appendix E table 11, which shows that there is no multicollionearity problem in this research[3].

[3] A VIF value above 10 may indicate multicollinearity, which is not the case (1.67).

Table 2: Correlation matrix of variables

	Credit~n	Total_~s	NPL	Automa~n	Digita~n	GDP	Year	Country	logCre~n	logTot~s	logNPL	logGDP
Credit_Pro~n	1.0000											
Total_Loans	0.9888	1.0000										
NPL	0.6007	0.7133	1.0000									
Automation	0.2255	0.2395	0.2236	1.0000								
Digitalisa~n	0.3533	0.3616	0.2776	0.5139	1.0000							
GDP	0.4877	0.5020	0.3988	0.2693	0.4166	1.0000						
Year	0.1785	0.2025	0.2466	0.7517	0.6404	0.2462	1.0000					
Country	-0.1537	-0.1481	-0.0713	-0.0676	-0.1149	-0.0608	-0.0048	1.0000				
logCredit_~n	0.6915	0.6956	0.4787	0.2325	0.2883	0.4010	0.1553	-0.0837	1.0000			
logTotal_L~s	0.6860	0.6982	0.5188	0.2600	0.3070	0.4162	0.1887	-0.0712	0.9912	1.0000		
logNPL	0.5855	0.6207	0.5757	0.3146	0.3413	0.4394	0.2669	0.0353	0.8486	0.8907	1.0000	
logGDP	0.3996	0.4150	0.3467	0.2929	0.3597	0.8949	0.2460	-0.0160	0.3945	0.4084	0.4342	1.0000

4.3 Empirical results

In this section the results for the three hypotheses are outlined. Before going into these results, first the Hausman test (1978) is performed to indicate whether a random effects or fixed effects model should be used for the panel dataset (Torres-Reyna, 2007). These are the most commonly used models for panel data estimators. This test is performed for the first two hypotheses, indicating that a fixed effects model best fits for the unbalanced panel data. The Hausman test can be found in Appendix E table 12 (total loans) and table 13 (NPL). Additionally, for every model a separate country fixed effect and bank fixed effect is tested for, since fitting both types of fixed effects in one regression results in collinearity problems due to the attributes of the independent variables, which are constant (Wooldrigde, 2013). Each regression result is provided with the number of observations, fixed effects, robust standard errors and R-squared.

4.3.1 Result hypothesis 1

Hypothesis 1 states that the implementation of new digital financial services by traditional banks led to an increase in the credit issuing to banking customers. Figure 1 in section 4.1 already showed an increase in total loans till 2008. However, this was done for all European banks combined and without the dummy variables $Automation$ and $Digitalisation$. As described in section 3.5, two models are performed in which the first model only includes the abovementioned dummy variables and the second model accounts for control variables. The results for both models can be found below.

Table 3: OLS regression results for hypothesis 1

	(**Model 2.1**) Total Loans	(**Model 2.2**) Total Loans	(**Model 3.1**) Total Loans	(**Model 3.2**) Total Loans
Automation	0.319^{***}	0.387^{***}	-0.122	-0.166^{*}
	(5.68)	(10.25)	(-1.10)	(-1.96)
Digitalisation	0.217^{***}	0.277^{***}	0.211	0.225^{*}
	(3.95)	(7.52)	(1.64)	(1.83)
GDP			0.736^{***}	0.841^{***}
			(4.24)	(4.02)
Constant	-0.301^{***}	-0.495^{***}	-0.0258	-0.228^{*}
	(-3.06)	(-6.97)	(-0.19)	(-1.71)
N	1669	1669	1621	1621
Year FE	no	no	yes	yes
Country FE	no	no	yes	no
Bank FE	no	no	no	yes
Robust s.e.	no	no	yes	yes
R^2	0.0552	0.172	0.138	0.397

Table 3 presents the OLS regression for hypothesis 1. Model 2.1 includes the sample without fixed effects and robust standard errors measured at country level. Model 2.2 does the same, except it is measured at individual (bank) level. Model 3.1 presents the sample with year and country fixed effects. Model 3.2 presents the sample with year and bank fixed effects. The reported values are the coefficients, the z-statistics are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$ indicate the statistical significance at the 10%, 5% and 1% respectively.

The standardized regression coefficients in model 2.1 and 2.2 are positive, meaning that that there is an increase in total loans when accounting for both automation and digitalisation processes within European banks. These coefficients are significant at the 1% level for the models without fixed effects (model 2.1 & 2.2). When incorporating year fixed effects together with country fixed effects (model 3.1), automation has a negative effect (-0.122) and digitalistion a positive effect (0.211) on total loans, yet these coefficients are insignificant. Model 3.2 with year fixed effects and bank fixed effects show equal signs of automation and digitalisation as model 3.1. However, the coefficients become significant at the 10% level. This indicates that both automation and digitalisation, when controlling for GDP, year and bank fixed effects, have a significant impact on the total loans for European banks. It can be noted that the number of observations (N) slightly decreases when controlling for GDP and fixed effects, but this does not lead to biased results. The last model (3.2) also has the highest R-squared (0.397), which shows that for 39,7% of the variance of total loans can be explained by the independent variables.

4.3.2 Result hypothesis 2

The second hypothesis expects an increase in NPL due to the better accessibility to credit by means of this digitalisation. The main reason for this expectation is that the low quality borrowers applying for a loan have more difficulty in fulfilling their repayment. Table 4 shows the results for hypothesis 2.

Table 4: OLS regression results for hypothesis 2

	(**Model 4.1**) NPL	(**Model 4.2**) NPL	(**Model 5.1**) NPL	(**Model 5.2**) NPL
Automation	0.344***	0.415***	0.136	0.148
	(5.71)	(8.34)	(0.62)	(0.80)
Digitalisation	0.341***	0.341***	0.0969	0.0613
	(5.80)	(7.04)	(0.59)	(0.47)
GDP			0.404*	0.446**
			(2.06)	(2.38)
Constant	-0.374***	-0.498***	-0.0994	-0.297**
	(-3.97)	(-7.99)	(-0.76)	(-2.02)
N	1669	1669	1621	1621
Year FE	no	no	yes	yes
Country FE	no	no	yes	no
Bank FE	no	no	no	yes
Robust s.e.	no	no	yes	yes
R^2	0.0771	0.135	0.131	0.233

Table 4 presents the OLS regression for hypothesis 2. Model 4.1 includes the sample without fixed effects and robust standard errors measured at country level. Model 4.2 does the same, except it is measured at individual (bank) level. Model 5.1 presents the sample with year and country fixed effects. Model 5.2 presents the sample with year and bank fixed effects. The reported values are the coefficients, the z-statistics are in parentheses. * *p* < .10, ** *p* < .05, *** *p* < .01 indicate the statistical significance at the 10%, 5% and 1% respectively.

As can be seen from table 4, there is an increase in NPL after the implementation of new digital financial services. In comparison to the first hypothesis, the coefficients for NPL have a higher positive value than for total loans for both automation and digitalisation in the models without fixed effects. Additionaly, similar to hypothesis 1, when the model is controlled for GDP and fixed effects, the results become less significant or even insignificant. However, when taking into account bank fixed effects, the explanatory power of the model does increase by roughly 10%.

4.3.3 Result hypothesis 3

The last hypothesis in this study expects that, despite the higher rate of NPL, banks will still be profitable, meaning that the increase in credit provisioning is higher than the increase in NPL. This hypothesis uses the logarithm of both total loans and NPL to indicate the percentual change of these components for European banks during the years they started offering new digital financial services. The results for the third hypothesis can be found in the graphs below and are explained further on.

Figure 2: Development credit provision for European banks in the period 1993-2018

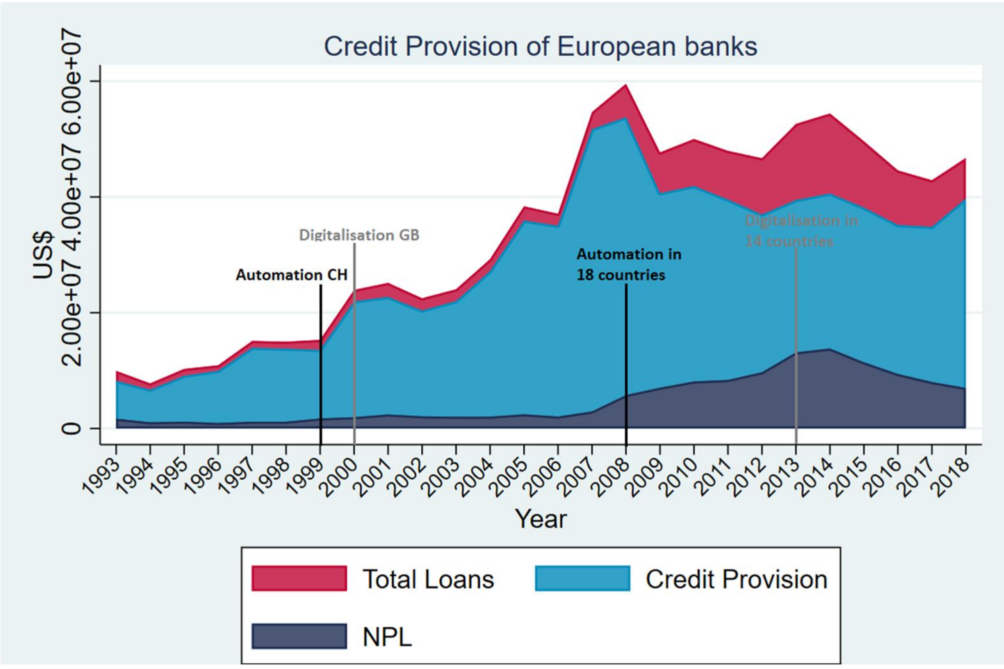
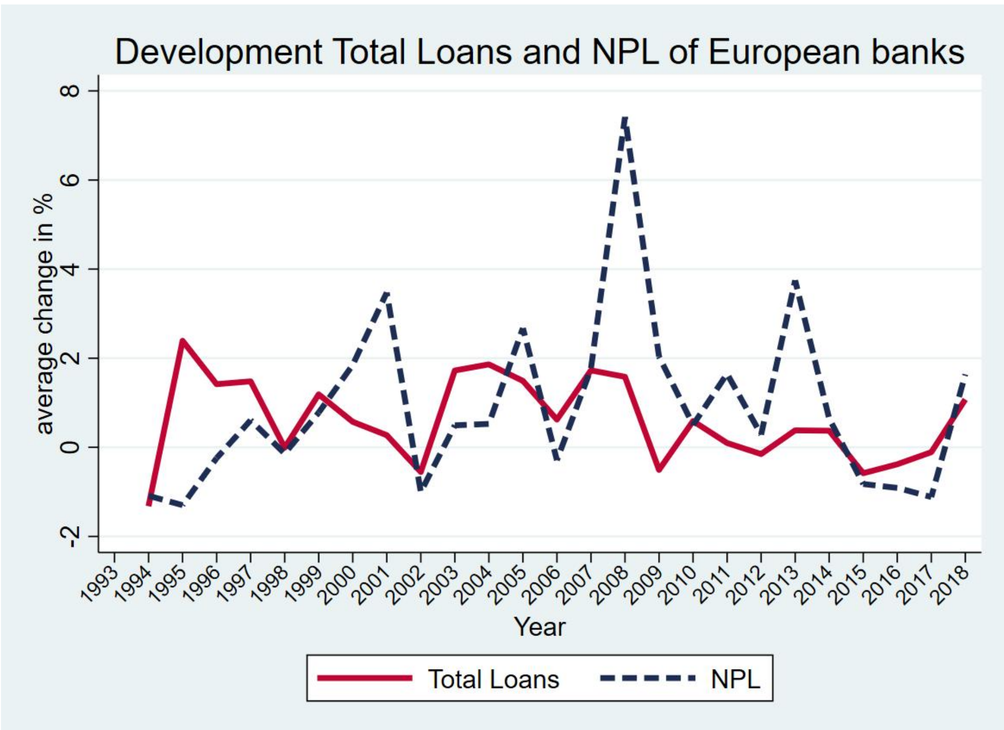


Figure 3: Development total loans and NPL for European banks in the period 1993-2018



In figure 2 it can be seen that the amount of loans has almost tripled in size in a timespan of 25 years, in which it almost shows exponential growth in the period 1993-2008. On the contrary, NPL remained relative steady till 2008, after it tends to grow in the next ten years. The credit provision in figure 2 (light blue) was the highest just before the financial crisis of 2008.

More interestingly might be the development of total loans and NPL of European banks depicted in figure 3. This figure shows the interrelationship between total loans and NPL during the sample period of 25 years. What stands out is the high percentage change of NPL in the years 2008-2009. This effect can be supported by the literature, confirming that since 2008, levels of NPL significantly increased (Makri *et al.*, 2014). Overall, the graph of NPL remains mostly above the graph of total loans, which indicates that European banks have become less profitable in providing credit to banking customers in the years they initiated offering new digital financial services.

4.4 Robustness checks

In addition to the regression results in the previous section, some robustness checks are performed to test the validity of the applied models. At first, an interaction term between automation and year ($Automation \times Year$) and digitalisation and year ($Digitalisation \times Year$) is performed. The reason for this interaction term is that it measures whether the effect of either automation or digitalisation is time dependent. The results give a main effect for these financial services, a main effect for year, and the interaction effect between financial services and year. Secondly, a slightly different robustness check is performed with lagged $Automation$ and $Digitalisation$, to see whether the implementation of these new digital financial services needed some time (1 year) to be fully adapted by European banks or became recognized by the banking customers.

Table 8 and 9 in Appendix D show the results with interaction terms for both total loans and NPL, respectively. The regression coefficients with the interaction $Automation \times Year$ show no significant results for total loans, whereas the interaction $Digitalisation \times Year$ does. Almost the same applies for NPL, but this component has more significant coefficients between $Automation \times Year$ than total loans does. Similarly, when accounting for lagged values of automation and digitalisation, the results stay more or less the same (table 10, Appendix D).

With regard to the hypotheses results in section 4.3, several robustness tests are done to see whether the results are not biased. It should be noted that the applied fixed effects in STATA automatically accounts for heteroscedasticity and autocorrelation through means of clustered standard errors, therefore eliminating unbiased estimations. Furthermore, the residuals of the independent variables are tested for normality. The results for these normality checks can be found in Appendix E, where some outliers can be seen in these plotted graphs. Therefore, an additional regression is done with the natural logarithms of the variables to eliminate these outliers. This outcome showed however no improvement of the model and has therefore been omitted.

5. Conclusion

This study primarily focused on the parallel relationship between the start of automation and digitalisation processes by European banks, thereby looking at how the total loans and NPL affected the credit provision for European banks. Other banking activities such as trading and investing (among others) have been excluded for this study to standardize the conceptual framework. Due to an increasing demand towards technology driven products, banks have been incentivized to participate in this digital revolution. Currently, the banking industry shows some similarities to the car industry, in which the traditional banks (petrol cars) have diminishing popularity and the new Fintech companies (electric cars, e.g. Tesla) gained popularity. Right now the banking industry is at an early stage of the digitalisation process, in which traditional banks need to make rapid and concrete decisions about how their future of banking will look like. Otherwise, digital platforms will gain market share at the expense of these traditional banks. The consumer behavior towards either reliability (traditional banks) or efficiency (Fintech) will be decisive for which one of the two options has the most potential to be sustainable in the future. This study investigated how new digital financial technologies implemented by European banks affected their credit provision.

Based on the results of this study, it can be concluded that since the start of automation and digitalisation processes by European banks, the amount of loans has increased, as well as the non-performing loans (NPL). This result was in line with the expectations. The third and last hypothesis, which stated that banks are still profitable despite the higher rate of NPL, is not supported by the regressions results. These results have shown that the increase in NPL is higher than the increase in total loans, meaning that the implementation of new digital financial services have caused more problems for banks to collect loan repayments. This phenomenon can be attributed to either low-quality borrowers applying for a loan, or the too low credit standards by banks. Nevertheless, the increasing credit defaults have caused a decrease in profitability for banks.

5.1 Limitations and future research recommendations

This study is one of the first to examine the effect of digitalisation for European banks using quantitative methods. Since almost no other quantitative studies on this topic exists, it is difficult to compare with previous research that only made a theoretical contribution. Therefore, this section will address multiple limitations for this study as well as give directions and recommendations for future studies.

First of all, it is rather difficult to adhere to all quantitative requirements when using an unbalanced panel-dataset. Unfortunately, the databases of BankFocus and Thomson One do not contain all the data for the included variables for all years, which is almost inevitable when dealing with 116 banks with a time period of 25 years. However, it must be noted that these missing data can be considered random, which can justify the methodologies applied. Besides, the obtained data for total loans and NPL could not be distinguished in size nor quantity, which makes it harder to validate the statements in the results. Subsequently, the high diversity in year initiation of these new digital financial services, as well as as the omission of some important control variables (e.g. interest rates and bank size) can lead to spurious or even biased results.These limitations in the availability of data and the chosen methodology to simplify the research question can weaken the external validity of the study. Another important note is that it is impossible to do regressions with country fixed effects and bank fixed effects together, since this leads to collinearity problems due to repeated values in the dataset. Notwithstanding, the results demonstrated that the overall effect of digitalisation on total loans and NPL is significant. In response to this statement, the results could become more valid if the countries are not pooled but handled individually. Therefore, a case study for each individual country in this dataset could have more meaningful insights on the impact of digitalisation processes of banks on the domestic credit market. Such case studies could also draw better conclusions about differences between banks in countries that already have or haven’t implemented automation and digitalisation in their business model.

To bring into perspective the effects of automation and digitalisation on the size or quantity of loans and NPL, it could be better to conduct a qualitative study adequated with a survey for banking customers in which they could indicate how digitalisation changed their perspective or behaviour when applying for a loan. A survey would be an appropriate research method to actually get to know how many banking customers used digital services by banks before they applied for a loan. Future studies could focus more on the customer perspective rather than the banking perspective by investigating whether the digital financial services of European banks have incentivized them to apply for a loan or that alternative (digital) credit platforms have offered them better deals. Another interesting direction for future studies is to look at the additional benefits or potential risks when going digital, such as better risk modelling or cybercrime, respectively. Going digital for banks should be a tool to boost convenience and user experience for banking customers, assisted with an increase in quality of service and a reduction in costs through better risk assessment. Ultimately, this should result in higher loans outstanding and lower NPL rates, however this study showed that since the implementation of automation and digitalisation processes, NPL rates also increased. Bearing in mind the adressed limitations mentioned above, the results of this study should therefore be carefully interpreted and used as a guideline for future studies.

6. References

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7. Appendices

Appendix A

TABLE 5: SUMMARY STATISTICS PER BANK

Country	#	Bank	ISIN code
Austria (5)	1	BK AUSTRIA CREDITAN	AT0000995006
	2	OBERBANK AG	AT0000625108
	3	BANK FUER TIROL UND	AT0000625504
	4	BKS BANK AG	AT0000624705
	5	ERSTE GROUP BANK AG	AT0000652011
Belgium (1)	6	KBC GROUP NV	BE0003565737
Switzerland (7)	7	UBS AG	CH0024899483
	8	EFG INTERNATIONAL	CH0022268228
	9	CEMBRA MONEY BANK AG	CH0225173167
	10	NEUE AARGAUER BANK	CH0003977193
	11	BANK CLER AG	CH0018116472
	12	BANK LINTH LLB AG	CH0001307757
	13	CREDIT SUISSE GROUP	CH0012138530
Cyprus (1)	14	HELLENIC BANK PCL	CY0105570119
Germany (5)	15	DEUTSCHE BANK AG	DE0005140008
	16	BAYER. HYPO- UND VER	DE0008022005
	17	COMMERZBANK AG	DE000CBK1001
	18	TF BANK	SE0007331608
	19	ING BHF-BANK AG	DE0008025008
Denmark (23)	20	DANSKE BANK A/S	DK0010274414
	21	JYSKE BANK A/S	DK0010307958
	22	SYDBANK A/S	DK0010311471
	23	SPAR NORD BANK	DK0060036564
	24	RINGKJ. LANDBOBANK	DK0060854669
	25	VESTJYSK BANK A/S	DK0010304500
	26	LAN & SPAR BANK A/S	DK0010201532
	27	DANSKE A	DK0060299063
	28	DJURSLANDS BANK A/S	DK0060136273
	29	SKJERN BANK A/S	DK0010295922
	30	SPAREKASSEN FAABORG	DK0010150523
	31	A/S GRONLANDSBANKEN	DK0010230630
	32	FYNSKE BANK	DK0060520377
	33	LOLLANDS BANK A/S	DK0060000107
	34	NORDFYNS BANK A/S	DK0010015072
	35	SALLING BANK A/S	DK0010017367
	36	KREDITBANKEN AS	DK0010253764
	37	TOTALBANKEN A/S	DK0060082758
	38	A/S MONS BANK	DK0060133841

	39	FIONIA HOLDING	DK0060129658
	40	DK COMPANY A/S	DK0010302488
	41	DIBA BANK A/S	DK0060076941
	42	LOKALBANKEN I NORDS.	DK0010312446
Spain (6)	43	BANCO BILBAO VIZCAYA	ES0113211835
	44	BANKIA SAU	ES0113307062
	45	BANCO SABADELL	ES0113860A34
	46	BANCO SANTANDER SA	ES0113900J37
	47	CAIXABANK	ES0140609019
	48	BANKINTER S.A.	ES0113679I37
Finland (4)	49	NORDEA BANK ABP	FI4000297767
	50	POHJOLA BANK	FI0009003222
	51	AKTIA BANK ABP	FI4000058870
	52	ALANDSBANKEN ABP	FI0009001127
France (6)	53	NATIXIS	FR0000120685
	54	STE. GENL. DE FRANCE	FR0000130809
	55	BNP PARIBAS SA	FR0000131104
	56	CREDIT LYONNAIS SA	FR0000184202
	57	CREDIT INDUSTRIEL	FR0005025004
	58	BANQUE TARNEAUD	FR0000065526
Greece (3)	59	ALPHA BANK SA	GRS015003007
	60	PIRAEUS BANK	GRS014003024
	61	GENERAL BANK OF	GRS002003010
Ireland (2)	62	BANK OF IRELAND	IE00BD1RP616
	63	AIB GROUP PLC	IE00BF0L3536
Iceland (2)	64	GLITNIR BANKI HF	IS0000000131
	65	LANDSBANKI ISLANDS	IS0000000156
Italy (14)	66	INTESA SANPAOLO SPA	IT0000072618
	67	BANCO BPM SPA	IT0005218380
	68	BANCA MONTE PASCHI	IT0005218752
	69	UNICREDIT SPA	IT0005239360
	70	MEDIOBANCA	IT0000062957
	71	CREDITO EMILIANO SPA	IT0003121677
	72	FINECOBANK	IT0000072170
	73	BANCA GENERALI SPA	IT0001031084
	74	BANCA CARIGE	IT0005108763
	75	BANCA IFIS SPA	IT0003188064
	76	BANCO DI SARDEGNA	IT0001005070
	77	BANCO DESIO BRIANZA	IT0001041000
	78	BANCA FINNAT EURAMER	IT0000088853
	79	BANCA PROFILO	IT0001073045
Malta (2)	80	BANK OF VALLETTA	MT0000020116
	81	HSBC BANK M P.L.C	MT0000030107
Netherlands (2)	82	ABN AMRO BANK	NL0011540547
	83	ABN AMRO HOLDING	NL0000301109
Norway (4)	84	SBANKEN ASA	NO0010739402

	85	FINANSBANKEN ASA	NO0003005001
	86	BANK2 ASA	NO0010273121
	87	DNB ASA	NO0010031479
Portugal (2)	88	BANCO COMERCIAL PORT	PTBCP0AM0015
	89	BANCO BPI, S.A.	PTBPI0AM0004
Sweden (3)	90	SKANDINAVISKA ENSK	SE0000148884
	91	SV. HANDELSBANKEN AB	SE0007100599
	92	JP BANK AB	SE0000192874
Turkey (12)	93	TURKIYE GARANTI BANK	TRAGARAN91N1
	94	TURKIYE IS BANKASI	TRAISCTR91N2
	95	AKBANK TAS	TRAAKBNK91N6
	96	TURKIYE VAKIFLAR	TREVKFB00019
	97	YAPI VE KREDI	TRAYKBNK91N6
	98	TURKIYE HALK BANKASI	TRETHAL00019
	99	QNB FINANSBANK AS	TRAFINBN91N3
	100	DENIZBANK	TREDZBK00015
	101	TURK EKONOMI BANKAS	TRATEBNK91N9
	102	SEKERBANK	TRASKBNK91N8
	103	ALTERNATIFBANK AS	TRAALNTF91N6
	104	ICBC TURKEY BANK	TRATEKST91N0
United Kingdom (12)	105	SANTANDER UK PLC	GB0000044551
	106	BANK OF SCOTLAND	GB0000764547
	107	BRADFORD & BINGLEY	GB0002228152
	108	METRO BANK PLC	GB00BZ6STL67
	109	SECURE TRUST	GB00B6TKHP66
	110	ALLIANCE & LEICESTER	GB0000386143
	111	HSBC HOLDINGS PLC	GB0005405286
	112	LLOYDS BANKING GROUP	GB0008706128
	113	BARCLAYS PLC	GB0031348658
	114	ROYAL BANK	GB00B7T77214
	115	STANDARD CHARTERED	GB0004082847
	116	CLOSE BROTHERS PLC	GB0007668071

Appendix B

TABLE 6: SUMMARY STATISTICS PER COUNTRY

		Year Initiated	
Country	**#Banks**	**Automation**	**Digitalisation**
Austria (AT)	5	2002	2012
Belgium (BE)	1	2007	2012
Switzerland (CH)	7	1999	2013
Cyprus (CY)	1	2012	2015
Germany (DE)	5	2002	2004
Denmark (DK)	23	2008	2013
Spain (ES)	6	2002	2008
Finland (FI)	4	2000	2007
France (FR)	6	1999	2003
Greece (GR)	3	2006	2014
Ireland (IE)	2	2007	2013
Iceland (IS)	2	2004	2017
Italy (IT)	14	2007	2014
Malta (MT)	2	2013	2017
Netherlands (NL)	2	2007	2012
Norway (NO)	4	2003	2013
Portugal (PT)	2	2009	2010
Sweden (SE)	3	2006	2013
Turkey (TR)	12	2003	2014
United Kingdom (GB)	12	2000	2000
Total	**116**		

Appendix C

TABLE 7: DESCRIPTION OF VARIABLES

Variable name	Measurement	Source
	Dependent Variable	
$Credit\_Provision$	The amount of credit that is available for banks after deducting the non-performing-loans (NPL) from the total loans, ceteris paribus*.	**N/A****
	Independent Variables	
$Total\_Loans$	Represents the total amount of money loaned to customers before reserves for loan losses but after unearned income. It includes but is not restricted to: Lease financing, Finance Receivables	**Thomson ONE*****
NPL	Represents the amount of loans that the bank foresees difficulty in collecting. It includes but is not restricted to: Non-accrual loans, Reduced rate loans, Renegotiated loans, Loans past due 90 days or more, Stage 3 Loans reported as part of IFRS 9. Past due loans under Stage 1 and Stage 2 reported as part of IFRS 9	**Thomson ONE**
$Automation$	Dummy variable which is equal to one when the bank has initiated to redesign their internal process, to save costs and improve their efficiency.	**Eikon******
$Digitalisation$	Dummy variable which is equal to one when the bank has initiated offering their financial services through digital products, such as online access through the internet or mobile phone applications.	**Eikon**
	Control Variables	
GDP	The monetary value of final goods and services, mostly used as a proxy for the country's economic health.	**Thomson ONE**
Country & year specific controls		
$Year\ FE$	Dummy variable which is equal to one for each specific year, which totals 25 dummy variables for the years 1993-2018.	**N/A**
$Country\ FE$	Dummy variable which is equal to one for each specific country, which totals 20 dummy variables for all countries.	**N/A**
Interaction effects		
$Automation \times Year$	The time-dependency of automation for European banks.	**N/A**
$Digitalisation \times Year$	The time-dependency of digitalisation for European banks.	**N/A**

* This is a simplified method to calculate the credit provision by banks. In reality, other factors may influence the credit provision.
** Generated by the regressions through STATA
*** Thomson ONE only denotes the variables in US dollars $
**** Eikon is used by selecting a sample of the banks within all countries.Then keywords in the bank's annual reports from 1993-2018 onwards are searched,such as 'automation', 'digitalisation', 'online banking', 'mobile applications' etc.

Appendix D

TABLE 8: OLS REGRESSION RESULTS WITH INTERACTION TERMS FOR TOTAL LOANS

	(1) *Automation* × *Year*		(2) *Digitalisation* × *Year*		(3) *Automation* × *Year*		(4) *Digitalisation* × *Year*	
GDP	0.784***	(3.77)	0.238	(1.44)	0.625***	(2.92)	0.0827	(0.25)
Year 1999	0	(.)			0	(.)		
Year 2000	-0.259	(-0.67)	0	(.)	-0.382**	(-2.11)	0	(.)
Year 2001	-0.283	(-0.78)	-0.000160	(-0.05)	-0.330*	(-1.87)	-0.00317	(-0.13)
Year 2002	-0.296	(-0.82)	0.0499**	(2.16)	-0.383**	(-2.22)	0.0235	(0.38)
Year 2003	-0.294	(-0.75)	0.149	(1.50)	-0.202	(-1.30)	0.472*	(1.72)
Year 2004	-0.280	(-0.66)	0.438**	(2.70)	-0.155	(-0.93)	0.714*	(1.93)
Year 2005	-0.183	(-0.44)	0.651***	(4.70)	-0.0148	(-0.09)	1.042**	(2.35)
Year 2006	-0.198	(-0.45)	0.812***	(6.76)	-0.0843	(-0.48)	0.924**	(2.11)
Year 2007	-0.0570	(-0.12)	1.632***	(3.85)	0.106	(0.54)	1.762***	(2.85)
Year 2008	-0.0626	(-0.12)	1.552***	(10.13)	0.202	(0.95)	1.983***	(3.45)
Year 2009	-0.0752	(-0.15)	1.294***	(8.80)	0.194	(0.98)	1.703***	(3.35)
Year 2010	-0.0404	(-0.08)	1.457***	(7.62)	0.241	(1.21)	1.873***	(3.72)
Year 2011	-0.163	(-0.32)	1.293***	(5.53)	0.157	(0.71)	1.788***	(3.39)
Year 2012	-0.143	(-0.29)	1.189***	(5.26)	0.160	(0.76)	1.701***	(3.35)
Year 2013	-0.132	(-0.25)	1.213***	(4.36)	0.151	(0.67)	1.678***	(3.11)
Year 2014	-0.150	(-0.28)	1.162***	(3.55)	0.148	(0.62)	1.674***	(3.01)
Year 2015	-0.125	(-0.23)	1.111***	(3.55)	0.151	(0.71)	1.595***	(3.13)
Year 2016	-0.198	(-0.37)	1.029***	(3.19)	0.104	(0.50)	1.539***	(3.03)
Year 2017	-0.277	(-0.52)	0.973***	(3.01)	0.0648	(0.30)	1.514***	(2.95)
Year 2018	-0.294	(-0.54)	0.997**	(2.78)	0.0634	(0.28)	1.553***	(2.89)
Constant	0.190	(0.41)	-0.709***	(-4.53)	-0.0259	(-0.16)	-1.083***	(-3.05)
N	1132		620		1132		620	
Country FE	**yes**		**yes**		**no**		**no**	
Year FE	yes		yes		yes		yes	
Bank FE	**no**		**no**		**yes**		**yes**	
Robust s.e.	yes		yes		yes		yes	
R^2	0.0798		0.0984		0.344		0.415	

Table 8 presents the OLS regression for total loans including the interaction terms. Model 1 and 2 represents the interaction between automation and digitalisation with year, respectively. Model 1 and 2 control for country fixed effects. Model 3 and 4 represents the interaction between automation and digitalisation with year, respectively. Model 3 and 4 control for bank fixed effects. The reported values are the coefficients, the z-statistics are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$ indicate the statistical significance at the 10%, 5% and 1% respectively.

TABLE 9: OLS REGRESSION RESULTS WITH INTERACTION TERMS FOR NPL

	(1) $Automation \times Year$		(2) $Digitalisation \times Year$		(3) $Automation \times Year$		(4) $Digitalisation \times Year$	
GDP	-0.119	(-0.38)	-0.854***	(-5.15)	-0.191	(-0.85)	-0.959**	(-2.26)
Year 1999	0	(.)			0	(.)		
Year 2000	-1.649**	(-2.80)	0	(.)	-1.974**	(-2.46)	0	(.)
Year 2001	-1.695***	(-2.95)	-0.0107***	(-3.33)	-1.969**	(-2.48)	-0.0127	(-0.78)
Year 2002	-1.703***	(-3.31)	0.168***	(7.26)	-2.009**	(-2.60)	0.149**	(2.23)
Year 2003	-1.504***	(-3.03)	0.371***	(3.41)	-1.730**	(-2.30)	0.562*	(1.81)
Year 2004	-1.448***	(-2.91)	0.732***	(5.02)	-1.661**	(-2.22)	0.886*	(1.95)
Year 2005	-1.423**	(-2.83)	0.828***	(4.39)	-1.605**	(-2.16)	1.064**	(2.12)
Year 2006	-1.447**	(-2.77)	0.911***	(3.69)	-1.660**	(-2.22)	1.023*	(1.68)
Year 2007	-1.516***	(-2.93)	1.595***	(4.45)	-1.691**	(-2.27)	1.752**	(2.10)
Year 2008	-1.215**	(-2.34)	1.902***	(8.49)	-1.343*	(-1.79)	2.228**	(2.43)
Year 2009	-1.086**	(-2.33)	1.865***	(9.12)	-1.219	(-1.63)	2.167***	(2.71)
Year 2010	-0.988*	(-2.09)	2.049***	(12.82)	-1.116	(-1.49)	2.354***	(2.84)
Year 2011	-0.969*	(-1.97)	2.098***	(11.92)	-1.069	(-1.42)	2.431***	(2.76)
Year 2012	-0.882*	(-1.78)	2.131***	(8.41)	-0.991	(-1.31)	2.485***	(2.94)
Year 2013	-0.607	(-1.30)	2.416***	(7.01)	-0.744	(-0.97)	2.754***	(3.31)
Year 2014	-0.552	(-1.13)	2.384***	(7.05)	-0.676	(-0.88)	2.741***	(3.34)
Year 2015	-0.759	(-1.66)	2.056***	(7.20)	-0.917	(-1.20)	2.354***	(3.25)
Year 2016	-0.909*	(-2.02)	1.892***	(6.41)	-1.055	(-1.40)	2.202***	(3.08)
Year 2017	-1.019**	(-2.26)	1.814***	(5.72)	-1.143	(-1.52)	2.134***	(2.94)
Year 2018	-1.104**	(-2.34)	1.784***	(6.11)	-1.225	(-1.63)	2.106***	(2.78)
Constant	1.259**	(2.88)	-1.003***	(-6.81)	1.423*	(1.91)	-1.243**	(-2.47)
N	1132		620		1132		620	
Country FE	**yes**		**yes**		**no**		**no**	
Year FE	yes		yes		yes		yes	
Bank FE	**no**		**no**		**yes**		**yes**	
Robust s.e.	yes		yes		yes		yes	
R^2	0.0739		0.0915		0.218		0.307	

Table 9 presents the OLS regression for non-performing loans (NPL) including the interaction terms. Model 1 and 2 represents the interaction between automation and digitalisation with year, respectively. Model 1 and 2 control for country fixed effects. Model 3 and 4 represents the interaction between automation and digitalisation with year, respectively. Model 3 and 4 control for bank fixed effects. The reported values are the coefficients, the z-statistics are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$ indicate the statistical significance at the 10%, 5% and 1% respectively.

TABLE 10: OLS REGRESSION RESULTS WITH LAGGED VALUES FOR AUTOMATION AND DIGITALISATION

	(1) Total Loans Automation		(2) Total Loans Digitalisation		(3) NPL Automation		(4) NPL Digitalisation	
L. Automation	-0.126	(-1.25)			-0.191	0.102		
GDP	0.614***	(2.84)	0.0969	(0.30)		-0.258	-1.004**	(-2.36)
Year 1999	0	(.)			0	0		
Year 2000	-0.415**	(-2.09)	0	(.)	-1.974**	-1.944**	0	(.)
Year 2001	-0.261	(-1.38)	-0.101	(-1.42)	-1.969**	-2.110***	-0.117	(-1.04)
Year 2002	-0.294	(-1.53)	-0.0765	(-0.75)	-2.009**	-2.103***	0.0516	(0.44)
Year 2003	-0.177	(-0.92)	0.330	(1.11)	-1.730**	-1.878**	0.452	(1.48)
Year 2004	-0.0333	(-0.16)	0.620	(1.58)	-1.661**	-1.762**	0.846*	(1.88)
Year 2005	0.133	(0.61)	0.936**	(2.02)	-1.605**	-1.695**	1.018**	(2.04)
Year 2006	0.0997	(0.44)	0.883*	(1.77)	-1.660**	-1.682**	0.996*	(1.67)
Year 2007	0.242	(1.14)	1.678***	(2.71)	-1.691**	-1.710**	1.691**	(2.04)
Year 2008	0.388	(1.57)	1.945***	(3.41)	-1.343*	-1.401*	2.201**	(2.41)
Year 2009	0.366	(1.45)	1.604***	(3.04)	-1.219	-1.280*	2.122***	(2.70)
Year 2010	0.417	(1.60)	1.780***	(3.40)	-1.116	-1.167	2.329***	(2.87)
Year 2011	0.332	(1.19)	1.680***	(3.04)	-1.069	-1.113	2.411***	(2.78)
Year 2012	0.334	(1.23)	1.605***	(2.99)	-0.991	-1.036	2.459***	(2.98)
Year 2013	0.325	(1.14)	1.615***	(2.88)	-0.744	-0.765	2.796***	(3.39)
Year 2014	0.322	(1.09)	1.591***	(2.72)	-0.676	-0.719	2.738***	(3.38)
Year 2015	0.325	(1.18)	1.478***	(2.66)	-0.917	-0.963	2.308***	(3.26)
Year 2016	0.272	(1.00)	1.422**	(2.56)	-1.055	-1.112	2.149***	(3.08)
Year 2017	0.238	(0.86)	1.400**	(2.50)	-1.143	-1.208	2.075***	(2.94)
Year 2018	0.232	(0.80)	1.430**	(2.44)	-1.225	-1.281*	2.052***	(2.80)
L. Digitalisation			0.0980	(1.22)			0.104	(0.95)
Constant	-0.0524	(-0.32)	-1.047***	(-2.97)	1.423*	1.419*	-1.242**	(-2.50)
N	1065		594		1065		594	
Country FE	no		no		no		no	
Year FE	yes		yes		yes		yes	
Bank FE	yes		yes		yes		yes	
Robust s.e.	yes		yes		yes		yes	
R^2	0.360		0.426		0.222		0.316	

Table 10 presents the OLS regression for the lagged values of automation and digitalisation for both total loans and NPL. Model 1 and 2 represents the lagged automation and digitalisation for total loans, respectively. Model 3 and 4 represents the lagged automation and digitalisation for NPL, respectively. The reported values are the coefficients, the z-statistics are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$ indicate the statistical significance at the 10%, 5% and 1% respectively.

Appendix E

TABLE 11: VARIANCE INFLATION FACTOR

Variable	VIF	1/VIF
Total_Loans	2.12	0.472303
NPL	1.82	0.548935
Digitalisa~n	1.56	0.639780
GDP	1.45	0.691264
Automation	1.38	0.723417
Mean VIF	1.67	

TABLE 12: HAUSMAN TEST FOR TOTAL LOANS

Hausman (1978) specification test

H_0: Constant variance	Coef.
Chi-square test value	70.348
P-value	0
Reject H0	YES

TABLE 13: HAUSMAN TEST FOR NPL

Hausman (1978) specification test

H_0: Constant variance	Coef.
Chi-square test value	7.691
P-value	.021
Reject H_0	YES

FIGURE 4: KERNEL DENSITY PLOT FOR TOTAL LOANS

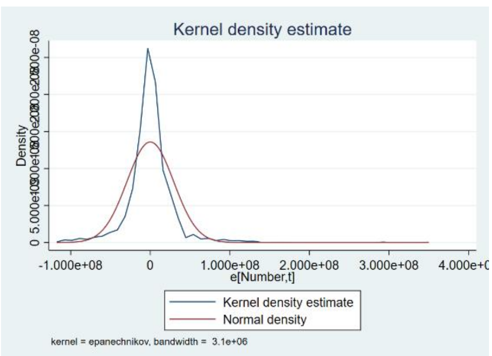

FIGURE 5: RESIDUAL VARIABLES AGAINST NORMAL DISTRIBUTION FOR TOTAL LOANS

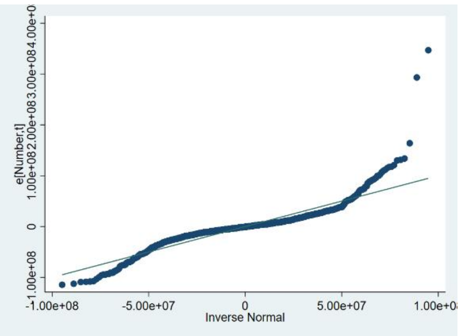

FIGURE 6: KERNEL DENSITY PLOT FOR THE LOGARITHM OF TOTAL LOANS

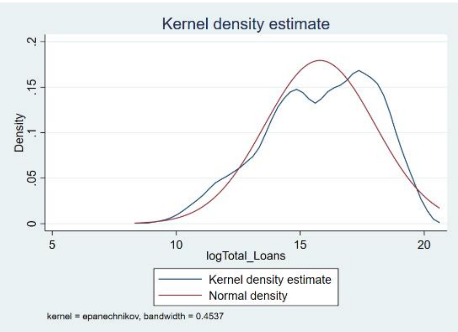

FIGURE 7: KERNEL DENSITY PLOT FOR NPL

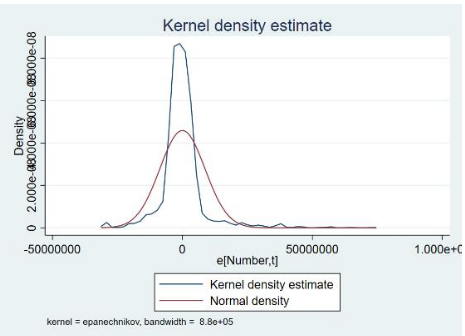

FIGURE 8: RESIDUAL VARIABLES AGAINST NORMAL DISTRIBUTION FOR NPL

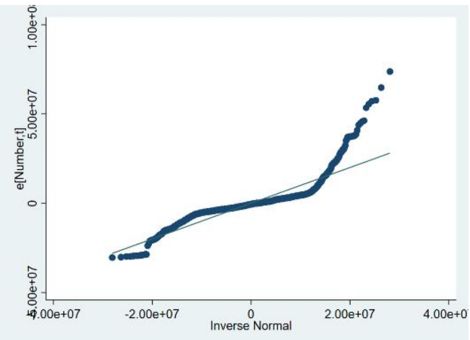

FIGURE 9: KERNEL DENSITY PLOT FOR THE LOGARITHM OF NPL