A three-phase comparative efficiency analysis of US and EU banks.

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Abstract

We examine the efficiency of European Union (EU) and U.S banks over the 2000-2018 period, where we divide our sample into three distinct time periods; pre-crisis (2000–2006), during (2007–2010) and post-crisis (2011–2018). We test for differences in technical efficiency based on size using the DEA method, where each region is sub-divided into four tiers of banking groups based on lending size. In addition to the DEA method, the effect of the financial crisis on banking efficiency is established through the Difference-in-Differences (DID) estimation, along with a Tobit estimation in an attempt to further examine the factors behind changes in efficiency. The findings from the research indicate that European banks are lagging behind the U.S in terms of technical efficiency, both before and after the crisis. Although the European banks are seemingly behind in terms of technical and scale efficiency, interestingly the European sector has actually grown by 16% from the period prior to the crisis, with the U.S posting a more modest 6% increase in efficiency. Our results are robust and further backed by the DID estimation, as we find a trend for increasing efficiency over time, however the results also show that the financial crisis had a negative impact on banking efficiency for the period with the overall difference of banking efficiency between the two trading blocs is the intensity of their transvariation. We find that the largest group of banks (S.I.Bs) can achieve higher technical efficiency by increasing their credit risk, while in contrast the smaller banks are rewarded by reducing their risk exposure further exacerbating thus the large divide among large and small banks. From a risk regulation perspective, the divergent behaviour, and the lack of common financial standards between EU and US banks, as evidenced by the divergent requirements imposed to the credit institutions, could affect both the competitiveness and the stability of the financial system. The implications of our results are of interest to the wider investing community, banking practitioners and regulators.

JEL Classification: G0, G2

Keywords: bank efficiency, US banks, EU banks, banking performance, risk regulation

1. Introduction

The last crisis sent the financial system into a recession on a global scale. More importantly, the crisis delivered a solid paradigm of the enduring interactions among banking markets and the real economy and has emphasised how various topical financial configurations can respond in a different way to shockwaves and regulatory policy actions. Unparalleled action was taken to introduce new regulations by the U.S. Federal Reserve System (Fed), the European Central Bank (ECB) and Basel Committee on Banking Supervision (BCBS) in order to preserve the necessary conditions for financial and economic stability regarding systemically important banks (SIBs). However, such exchanges among banking markets and the real economy are fundamentally reliant not only on financial regulation dimensions such as the quality of the underlying supervision and regulation, but also on the way those financial markets compete and interact with one another. The institutional composition of banking markets, their *modus operandi*, the banking regulations and the repartition between large and small banking institutions also had an impact on tightening credit, restricting growth, financial stability, market convergence and the recovery processes.

It is generally assumed that integrated and converging markets - in particular, convergence as it relates to efficiency in cost and profit - results in a better allocation of resources, resulting in higher productivity, efficiency and effectiveness (Jeon et al., 2011; Casu and Girardone, 2010,2009,2006; Kondeas et. al 2008). However, in the aftermath of the crisis, major banking markets have also diverged from one another with the evolution of the banking efficiency following a differential path among competing markets. The outbreak of the financial crisis interrupted the convergence process of international banking markets and gave rise to a new divergence process (Gallizo et al., 2016). Over the last 10 years, following the crisis, the American banking sector has attained a cumulative positive profitability of 70%, whereas the European counterpart sector – the largest banking system in the world - has provided for a cumulative negative return of 60% (ECB, 2019). This startling asymmetry may point among others to the asymmetrical efficiency of regional banks being highly relevant both for financial stability and credit growth (Huljak et al., 2019). Other authors that have analysed the impact of bank efficiency and growth across Europe before and during crisis times without assessing post-crisis effects show that bank efficiency is positively and significantly related to regional growth and call for more research in this field (Belkea et al., 2016). Our study is in line with the latest research that calls for further research in banking efficiency (i.e. Sousa de Abreu et al., 2019) and contributes to integration studies at an international level.

Previous studies, for a large part are either largely focused on a single country (i.e. the USA) or the single market (i.e. the EU) and limit the research to a period of two to three years following the crisis with a highly varying degree as to the samples utilised, the choice of methods and types of efficiency examined. Rather than pursuing a pure focus on selected efficiencies and within a specific market or region, this research seeks to fill an important gap in the field of study through estimating a more inclusive and updated sample as well as various dimensions of efficiency in three economic phases. Additionally, we further examine the credit risk of financial holding companies and banking groups in the aforementioned financial blocks. This

is measured through a Data Envelopment Analysis (DEA), where the impact of the financial crisis is assessed using the difference-in-differences estimation. Furthermore, a Tobit regression is used to elucidate the factors behind changes in efficiency. The research therefore attempts to explicate how the changes in regulations have affected the credit channel as a whole through liquidity provision and risk-management.

Our work contributes to the extant empirical literature in four ways. First, we use an updated bank-level data-set for 2 major, global markets with both policy and research implications. Second, we explore a set of bank features which allow us to draw important policy implications for the US and EU banking systems. Third, we provide for an updated assessment and tracing of efficiency scores during three distinct economic phases in these two markets. Using the interaction of all the bank characteristics with a crisis dummy allow us to find different influences of several variables on the banks' efficiency in stress periods in comparison with the tranquil ones (pre- and post-crisis). Fourth, we draw meaningful distinctions between large and small banks where our results are also useful for investors and policymakers when designing a proper institutional framework.

Our paper is structured as follows: Section 2 provides a review of the major literature in the area; Section 3 outlines the methodology; Section 4 presents the empirical results; finally, Section 5 offers some concluding remarks.

2. Literature review

Efficiency studies have long ago shown that financial institutions can be identified as decision-making units (DMU`s), where the best performing DMU`s operate on the efficient frontier which functions as a best practise benchmark through the DEA model (Charnes et al., 1978). Studies of this type are intended to rank the institutions based on their efficiency scores or alternatively measure scale inefficiencies. The research so far on banking efficiency shows mixed results among studies even where the same period or the same markets have been examined. Authors have long argued that there is no universal agreement as to the selection of variables that further increase the reliability of efficiency studies and they attribute the difference in results based on the choice of model and approach (Miller and Noulas, 1996).

Starting as early as the 1980s and early 1990s, studies focus on employees and capital as inputs, while loans made up the main part of the output the authors found U.S banks at the time to be highly allocatively efficient, rather than technically efficient (Aly, et al., 1990; Hancock, 1986). Wheelock and Wilson (1999) research the technical and scale efficiency of U.S commercial banks from 1984 to 1993, along with the productivity of the U.S banking sector, in a period where the U.S market went through a large number of bank failures along with new regulations and technological changes to the banking system. They find clear evidence for a decline in efficiency from the start of the period where smaller banks were highly inefficient, while larger banks operated at a more efficient level. This is also in line with studies showing a general decline in cost efficiency from 80% prior to 1990 down to 77% for the period 1990 – 1995 in the U.S banking industry (Berger and Mester, 1997).

Studies in the EU find lower efficiency levels in the EU banking sector, with significantly lower efficiency across the 10 countries in the study with an average

score of 62% for 1993 (Lozano-Vivas et al., 2002). The authors argue that environmental variables account for differences in the countries. Over the same period research had found similar levels of efficiency in the European Union when inspecting a total of 257 banks in 7 countries with an average efficiency of 63% (Pastor et al., 1997). The same research indicates different results from U.S bank oriented research operating at a slightly lower 63.5% as opposed to 77% for the 1990-1995 period (Berger and Mester, 1997).

For the period 1997–2003 the efficiency of the 15EU countries is found to be 77.72% demonstrating a significant difference in efficiency levels (Casu and Girardone, 2006). However, over a similar period (1996-2003) authors find the technical efficiency of EU banks scales much higher indicating an overall technical efficiency of 87.84% (Brissimis et al., 2010). This difference can be attributed to several reasons, as researchers were able to select among a wide range of methods and variables: DEA, Distribution Free Approach (DFA), Stochastic Frontier Analysis (SFA) and Bayesian Estimation (BE), amongst others. It also points to the argument made above with regards to no universal agreement on appropriate methods and input-output variables.

The prelude to the crisis and the changing financial landscape over time due to regulations has also been examined by various studies. Research analysing the period from 2001 to 2009 employing the intermediation approach focuses on variable returns to scale. The authors find that deposits along with labour and capital for the production of earning assets and loans affect significantly the cost and profit efficiency levels of banks; the average efficiency level for the period is found to be 72% for banks in the 27 EU member states. For the same period, they also find of increasing efficiency across the EU region (Chortareas et al., 2013). A similar study, focusing though on US bank holding companies further investigates the relationship between banking efficiency and diversification from 1997 – 2007 where the financial system was also deregulated to allow financial holding companies to diversify, increase and widen operations, while increasing the efficiency of the business (Elyasiani and Wang, 2012). The study finds that the effect of deregulation on efficiency is limited. Furthermore, the average technical efficiency for the period is 79.6%, which indicates comparatively similar performance to EU banks yet also indicates a slight stagnation based on the previous results from research discussed above (Wheelock and Wilson, 1999; Berger and Mester, 1997).

More recently, a range of studies have been conducted on the effects of the U.S. subprime crisis on EU banks, and the transition into the global financial crisis of 2007-2010. A research utilizing a two-stage DEA model, where the deposits are used as an intermediate variable rather than input or output, supports that the EU28 experienced a drop in efficiency and productivity growth when the global financial crisis started. Furthermore, the results indicate that the same trend continued into the sovereign debt crisis with evidence of credit constraints and lending activities over the period (Degl`Innocenti et al., 2017). These results are in line with research showing that European banks are seen as less scale efficient than their U.S counterparts, with a clear decline in scale efficiency over the period of the crisis. However, throughout the period from 2004 to 2014, there are also clear indications of EU banks experiencing consistently higher technical efficiency characterized by declination after the crisis (Feng and Wang, 2018). This decline is attributed to a shift

in the focus of EU banks where the decrease in international activity is substituted by domestic investments. Importantly, the authors argue there are two major reasons behind the change in efficiency. Firstly, EU banks have devoted more resources to fully comply with Basel III put in place due to the crisis, and secondly due to higher costs of funding and non-performing loans. This also points to a divide between US and EU banks with regards to regulatory compliance. EU banks seem to be disadvantaged by fully absorbing and suffering the costs of regulation.

Another strand of research attempts to reveal whether efficiency helps banks during financial crises and/or whether regulatory interventions to stabilise banks affect efficiency either way. A characteristic of such studies is that they split their analysis into "normal" and "crisis" times, allowing them to see changes in both efficiencies during both time periods. Authors show that high cost efficiency is associated with increased management effort during crises. They suggest that decision makers could decide to focus on cost efficiency under normal times, in order to increase their performance during the crises (Assaf et al., 2019). Institutional and regulatory interventions such as the ECBs QE can also initiate processes to strengthen banks and stabilize the financial system. Such research examines the relationship between risks and efficiency while controlling for the effect of quantitative easing (QE) on the level of efficiency. Changes in monetary policy diminish banking efficiency on commercial banks. Regulatory policy interventions such as QE might not be an effective tool for the strengthening of bank performance. Topical market configurations such as competition structure and bank-specific characteristics actually account for a larger proportion of a bank's efficiency levels (Mamatzakis et al., 2016).

The majority of bank efficiency studies are focused on the early stages of 2000s and the period leading up to the financial crisis (Doan et al., 2018). These studies are conducted on the years before the global financial crisis and just a few surrounding years not surpassing 2012 in their majority. As shown, in the most current research, there are strong calls for extending the research further (Assaf et al., 2019; Huljak et al., 2019; Sousa de Abreu et al., 2019; Doan et al., 2018; Degl`Innocenti et al., 2017). We find that there is still a lack of research on the longer period following the latest global financial crisis and the implementation of Basel III. Therefore, as another contribution to the existing literature, we seek to utilize the DEA method in a three-stage process to explore the efficiency of EU and U.S banks before and after the crisis, in an extended and inclusive sample for a comparative analysis of the two regions.

3. Data, Methodology and Descriptive Statistics

3.1 Data

We collect consolidated financial data on bank holding companies and banking groups (henceforth referred to as banks) from the 28 countries in the European Union and the Unites States. For the EU member states, we sample data from 52 banks, and a further 70 banks from the U.S for a total sample of 122 banks following the criteria of sample homogeneity as the companies are operating simultaneously in the financial sector (Canhoto and Dermine, 2003). As the EU sample only consists of banks from countries that are a member state of the European Union, EEA countries and other non-EU members are excluded. The paper utilizes annual financial data available on a selection of platforms over the period 2000-2018. We require that the

data is simultaneously present in Bloomberg, DataStream and Thomson One for cross-checking and clarity purposes. Where the platforms used have not been able to provide full information, data have been manually filled through the posted annual consolidated financial statements found on the respective companies' website. For the institutions that we were unable to retrieve complete sets of data, these have been removed from the sample due to lack of completeness for the chosen variables, in accordance with established research requirements (Holod and Lewis, 2011; Laeven et al., 2016). To further support the empirical estimation following the main analysis, the European holding companies and banking groups have their data collected in US Dollars (USD) for a homogenous dataset, which is applied in the respective platforms.

3.2 Data envelopment analysis

Technical efficiency has been very early on described as the success of a firm with maximizing the outputs, using a given set of inputs (Berger and Humphrey, 1997). On the basis of the chosen inputs, the DEA method calculates a specific level of output which serves as the total level of technical efficiency. The method seeks to employ a frontier which serves as a benchmark for the comparison relative to the frontier. The main concepts of efficiency include technical, allocative, scale, cost, profit and alternative profit efficiency. We follow established, seminal research investigating the impact on efficiency where we apply the non-parametric DEA approach to measure technical efficiency of DMU`s in the two markets (Berger and Mester, 1997; Berger and Humphrey, 1997). Each individual DMU is juxtaposed against the point of reference which provides the overall technical efficiency and scale inefficiency. Our focus is on constant returns to scale (CRS) and variable returns to scale (VRS). The addition of VRS can reveal the optimum scale of operation of the decision making units (DMU`s). The VRS is therefore utilized to discover scale inefficiencies while mitigating the effect size has on the estimation of efficiency and the scale inefficiencies of both markets can be estimated (Holod and Lewis, 2011; Coelli, 1996). For the selection of variables, it is important to consider the approaches available in the literature on banking efficiency. The two main approaches are the production approach and intermediation approach. The production approach usually measures how a bank is able to produce transaction services based on the inputs, which for the approach is mainly capital and labour. On the other hand, the intermediation presumes that the bank aggregates loans and other income based on the creation of customer deposits, number of employees and consumption of total assets for inputs Paradi et al., 2011). However, there is little to no consensus for a definitive set of variables used for outputs in either of the methods and the variables of the model often vary due to availability of data (Doan et al., 2018; Miller and Noulas, 1996). The linear programming problem to solve for the DEA results is given by Coelli (1996):

$$
\begin{aligned}
& min_{\theta}\theta, \\
& s.t. \qquad -y_{it} + Y_{t,j}\lambda \geq 0 \qquad (1) \\
& \theta X_{it} - X_{j,t}\lambda \geq 0 \\
& \lambda \geq 0
\end{aligned}
$$

Where θ equals the efficiency score of the DMU, and 1 is seen as perfectly technical efficient with a placement on the efficiency frontier. In the continuation of calculating variable return to scale (VRS) and scale inefficiencies, this suggests an additional constraint $N1'\lambda = 1$, to be added to (1) above. The constraint is given as:

$$
\begin{aligned}
& min_{\theta}\theta, \\
& s.t. \qquad -y_{it} + Y_{t,j}\lambda \geq 0, \\
& \theta X_{it} - X_{j,t}\lambda \geq 0, \qquad\qquad (2) \\
& 1'\lambda = 1 \\
& \lambda \geq 0
\end{aligned}
$$

Banker et al. (1984) have shown that the CRS measure of efficiency can be expressed as the product of a technical efficiency measure and a scale efficiency measure. Put simply, a broad interpretation of efficiency can be stated as: industry or cluster A (i.e. EU banks) is more efficient structurally than industry B (i.e. USA banks), if the distribution of its best firms is more concentrated near its efficient frontier for industry A than for B. We utilise an input-oriented method that allows the use of multiple inputs without imposing any functional form on data or making assumptions of inefficiency. In the banking literature, production-oriented DEA models have been utilised for identifying inefficiency as a proportional increase in production use (Miller & Noulas, 1996; Grönroos and Ojasalo, 2004). Earlier, Banker (1984), Banker et al. (1984; 2004) show how a comparison of two different efficiency measures (i.e. input vs. output oriented models) reveals the nature of (local) returns to scale at the input-oriented projection of an inefficient input-output bundle on to the frontier of the production possibility set. Subhash, (2008) argues that when the technology exhibits constant returns to scale (CRS) globally, input- and output oriented radial measures of technical efficiency are identical. If this equality does not hold for every input-output bundle, the technology is characterized by variable returns to scale (VRS).

Regarding the VRS LP this approach forms a convex shape that encircles/envelopes the observations more densely than the CRS approach and provides for technical efficiency scores which are either greater (or at the very least equal) to those generated by the CRS model. This particular model specification has been consistently used since the 1990's since it calculates efficacies that are *'clean'* of scale efficiency effects and this what we also aim to achieve by using these specifications as in equations 1 and 2. When the production possibility set is convex, if the technology demonstrates topical diminishing returns to scale at smaller input scale, then it cannot exhibit increasing returns are at a larger input scale. This is also something that is implicitly argued further below in our analysis. There we argue that efficiency is not only dependent on inputs/outputs but also on structural and regulatory differences between market settings where changes in inputs/outputs are less dependent on institutional strategy and more dependent on operational issues. Cullinane et al, (2005) argue that in general, input oriented models focus more on operational and managerial issues whereas output-oriented models are more associated with planning. This is even more prevalent today. In the present disruptive financial technology and banking sector operational redesign most of the banks continuously keep reviewing their operational capacity utilization in order to ensure the provision of better services to the society and users.

3.2.1 Analysis framework

We implement a three-step process where initially the DEA estimation determines the level of efficiency of the sample. In addition to technical efficiency, we assess scale inefficiencies indicating slack within the DMU`s utilization of inputs and outputs. While the first part of the analysis provides information on differences among the DMU`s in the sample, the method does not allow for an effective estimation of changes in efficiency due to changes in the economic environment. Hence, for the second part of the procedure we employ the Difference-in-Differences (DiD) estimation. The DiD model takes foundation in the DEA results, which in turn enable for isolation of an event, and estimation of its effect on the sample. For the third and final step we run a Tobit regression based on the results obtained in the DID approach. The Tobit utilises the results from the initial analysis to screen for a selection of independent control variables and their relationship towards the dependent variable and exhibiting the underlying factors of change in efficiency.

3.3 Pooled DEA sample criteria and descriptive statistics

The data is treated as pooled data, where both cross-sectional and time series data are being utilized. This allows for the data to be pooled into one sample, where we can calculate the average efficiency level for a given year, which in turn enables for tracking of changes in efficiency (Canhoto and Dermine, 2003). A pooled sample allows for measuring the average efficiency score for the US and EU in all three phases. The sample constituents are regarded as financial holding companies and banking groups and from the specification the sample of banks will be divided into four groups for both markets. The three main groups are based on size, while an additional group is added to assess the efficiency of systemically important banks (S.I.Bs henceforth) where our grouping is based on total lending in table 1 below as per the Financial Stability Board (FSB, 2018).

Table 1. Banking Groups by lending

Groups	Lending*
Group 1	$10
Group 2	$10≤Lending≤$50
Group 3	≥$50
S.I.Bs	FSB**

* Billion USD

** As specified with the FSB

The structuring of banks into separate groups allows for more effective comparison between distinct tiers of the market, and a comparison of efficiency levels between different levels of size. Banks that are listed with the Financial Stability Board's listing (FSB) are therefore placed into a separate group and not included in the largest group (FSB, 2018).

Input and output selection

We follow the intermediation approach, since this approach is considered more suitable for financial institutions (Berger and Mester, 1997; Berger and Humphrey, 1997). Accordingly, the selection of input and output variables are based on previous established research utilizing the intermediation approach (Aly et al., 1990; Berger and Mester, 1997; Pasiouras, 2008b; Doan et al., 2018; Assaf et al., 2019). The inputs are primarily number of employees, deposits and fixed assets (property, plant and equipment). Outputs consist of the total number of loans and other income. The variables are in line with the standard intermediation approach based on the data available. With a total of 122 banks between the two markets, the following variables in table 2 are used as inputs (X) and outputs (Y) for the efficiency estimation:

Table 2. Input/output DEA Variables

Inputs (x)	*Variable*	*Outputs (y)*	*Variable*
Employees	x_1	Loans	y_1
Fixed Assets	x_2	Other Income	y_2
Deposits	x_3		

Efficiency scores are estimated with both CRS and VRS, in order to estimate for scale inefficiencies along with the ability to reduce the impact of bank size using variable return to scale (Holod and Lewis, 2011). The input-output descriptive statistics by region are shown in table 3 below.

Table 3. DEA Input-Output descriptive *statistics* for EU and USA

	Variable	*Obs.*	*Mean*	*St. Deviation*	*Min.*	*Max.*
Europe	Loans	988	197117.31	252781.55	31.29	1656918.6
	Other income	988	5625.081	10231.538	-7804.41	91075.852
	Deposits	988	167855.01	242932.54	52.87	1482812
	Fixed Assets	988	3293.336	5696.196	0.8	37175.629
	Employees	988	41561.782	56154.397	74	315520
USA	Loans	1330	60454.043	163595.08	12.41	993993
	Other income	1330	3067.724	9050.852	-89	72534
	Deposits	1330	74050.172	208849.01	22.54	1470666
	Fixed Assets	1330	956.096	2342.714	0	18317
	Employees	1330	19626.237	53011.61	44	374000

3.3.1. Input-Output Robustness

Our 3input-2output combination is drawn from well-established literature in the domain of efficiency studies. Although within the contemporary literature there is no universally agreed standard for numbers and selections of inputs and outputs, it is well known that the efficiency scores are very sensitive to different input/output selections. In order to gauge the robustness of our results, we have added a third output variable. Established research (Assaf et al., 2019; Degl'Innocenti & Asaftei, 2008) have consistently utilized securities as an output variable amongst others such as loans, interbank assets and off-balance sheet assets. Including securities as the third output, our findings suggest the results in the model are robust as there is no

significant difference between the two market estimations as can be seen from tables 4 and 5 that follow (Group 1 = With Securities and Group 2 = Without Securities).

Table 4 – Independent Sample Test for differences EU sample

Group Statistics					
	Group	N	Mean	St. Deviation	St. Error Mean
CRS_EU	1	988	0.55243	0.251401	0.007998
	2	988	0.53205	0.244695	0.007785

Independent Samples Test											
		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence interval of the Difference	
		F	Sig.	t	df	one-sided p	two-sided p	Mean diff.	St. Error Diff.	Lower	Upper
CRS_EU	Equal variances assumed	1.698	0.193	1.826	1974	0.034	0.068	0.2038	0.01116	-0.001508	0.042270
	Equal variances not assumed			1.826	1972.6	0.034	0.068	0.2038	0.01116	-0.001508	0.042270

Independent Samples Effect Sizes					
				95% Conf. Interval	
		Standardizer (a)	Point Estimate	Lower	Upper
CRS_EU	Cohen's d[1]	0.248071	0.082	-0.006	0.170
	Hedge's correction[2]	0.248165	0.082	-0.006	0.170
	Glass's delta[3]	0.244695	0.083	-0.005	0.172

a. The denominator used in estimating the effect sizes.

Cohen's d uses the pooled standard deviation.

Hedge's correction uses the pooled standard deviation, plus a correction factor.

Glass's delta uses the sample standard deviation of the control group.

[1] Cohen's d suggests that a d around 0.2 is considered a 'small' effect size, meaning that if the difference between two groups' means is around or less than 0.2 standard deviations, then difference is negligible, even if it is statistically significant (see Ellis, 2010).

[2] Hedges' g is sometimes called the corrected effect size and it is applied as in Cohen's d above when sample sizes are below 20 observations (ibid).

[3] Glass's delta, which uses only the standard deviation of the control group, is an alternative measure if each group has a different standard deviation. As shown this is not the case through our robustness tests (ibid).

Table 5 – Independent Sample Test for differences US sample

Group Statistics					
	Group	N	Mean	St. Deviation	St. Error Mean
CRS_US	1	1329	0.77870	0.130570	0.003582
	2	1330	0.71761	0.142848	0.003917

Independent Samples Test											
		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence interval of the Difference	
		F	Sig.	t	df	one-sided p	two-sided p	Mean diff.	St. Error Diff.	Lower	Upper
CRS_US	Equal variances assumed	1.885	0.170	11.509	2657	<0.001	<0.001	0.061087	0.005308	0.050679	0.071495
	Equal variances not assumed			11.509	2636.1	<0.001	<0.001	0.061087	0.005308	0.050680	0.071494

Independent Samples Effect Sizes					
				95% Conf. Interval	
		Standardizer (a)	Point Estimate	Lower	Upper
CRS_US	Cohen's d	0.136849	0.446	0.369	0.523
	Hedge's correction	0.136888	0.446	0.369	0.523
	Glass's delta	0.142848	0.428	0.350	0.505

a. The denominator used in estimating the effect sizes.

Cohen's d uses the pooled standard deviation.

Hedge's correction uses the pooled standard deviation, plus a correction factor.

Glass's delta uses the sample standard deviation of the control group.

3.4 Difference-in-Difference Estimation

The difference-in-differences (DID) model is one of the more significant tools in applied research economics where the model can be used as a linear or non-linear method for the estimation of terminal effects due to policy changes or other changes in the economic environment (Puhani, 2012). The model works on several assumptions, where the estimation is based on observation of a control group and a treatment group over a time period. The treatment group is given value equal to 1,

which is compared to the control group over time period T. The groups and time period of the model are specified as below:

$$G_i = \begin{cases} 0 \; if \; bank \; i \; belons \; to \; control \; group \\ 1 \; if \; bank \; i \; belongs \; to \; treatment \; group \end{cases} for \; i = 1, \dots, N = N_{USA} + N_{EU} \qquad and$$

$$T_t \begin{cases} 0 \; if \; period \; belongs \; to \; a \; control \; subepriod \\ 1 \; if \; period \; belongs \; to \; a \; treatment \; subperiod \end{cases} for \; t = 1, \dots, T \qquad (3)$$

Following Athey and Imbens (2006) the benchmark model for the D-I-D construct is as follows: the particular *i* belongs to a group $G_i \in \{0, 1\}$ (where group 1 is the treatment group) and it is observed in time period $T_i \in \{0, 1\}$. For i = 1…,N, a random sample from the population, individual *i's* group identity and time period can be treated as random variables. Following that, letting the outcome be say Y_i, the observed data are the triple (Y_{it}, G_i, T_t). Following from this, the general D-I-D model constant across time and population is defined as in Puhani (2012):

$$Terminal \; Effect = \mathrm{E[Y|G = 1, T = 1, X] - E[Y|G = 0, T = 0, X]} \qquad (4)$$

Following Lindlbauer et al., (2016) the empirical specifications for the model is presented in accordance:

$$y_{it} = \beta_0 + \beta_1 G_i + \beta_2 T_2 + \beta_3 G_i T_t + \varepsilon_{it} \qquad (5)$$

Where:

$y_{i,t} = Efficiency \; at \; time \; t \; for \; entity \; i$

$\beta_0 = Intercept$

$\beta_1 = Group \; effect$

$\beta_2 = Subperiod \; effect$

$\beta_3 = Interaction \; effect$

$\varepsilon_{iT} = Regression \; Error \; term$ with $e_{i,t} \sim N(0,\sigma)$.

It has been shown that the Ordinary Least Squares (OLS) regression brings forth a hindrance as the model does not properly deal with restricted variables (Doan et al., 2018; Gorman and Ruggiero, 2008). Because of the truncated distribution of the dependent variable from a DEA analysis, the Tobit model is introduced. The Tobit model is a censored regression and can therefore censor for a specified value on the left (minimum) or right side (maximum) of the regression. Especially when operating as part of a DEA process, where the DEA score does not exceed 1. Therefore, the Tobit model can be implemented in the process and estimated with the following equation in matrix notation (Loikkanen and Susiluoto, 2002):

$$Y_{it} = \begin{cases} 1 \; if \; Y_{it}^* \geq 1 & (6) \\ Y_{i,t}^*, if \; 0 < Y_{i,t} < 1 & (7) \\ 0, \; if \; Y_{i,t} \leq 0 & (8) \end{cases}$$

Where: $Y_{it}^* = X_{it}\beta + \varepsilon_{it}$ where $X_{it} = (1, G_i, T_t, G_i T_t)$ and $\varepsilon_{it} \sim N(0,\sigma)$

Although both models share some similarities, the Tobit method is more desirable due to its nature as a censored regression. While the OLS method is still considered by some to be a better option rather than Tobit, numerous studies utilize both OLS and Tobit regression in order to examine the first part of the analysis as well as point out robustness in estimation differentials (Gorman and Ruggiero, 2008; Kempkes and Pohl, 2006). In this part of the analysis, the DiD estimation utilizes the same time period from 2000 to 2018, with a slight altercation. As one of the main aspects of the analysis is geared towards examining the effects of the crisis on European and U.S banks, it is important to clearly identify the time period of the crisis. According to research, the empirical estimation uses the period 2007–2010, as the time of the global financial crisis (Liu and Ngo, 2014). Therefore, the GFC is excluded from the sample to account for the treatment effect. The approach estimates the difference between the control and treatment group, and therefore allows for measurement of the terminal effect of the US subprime mortgage crisis, in the attempt to explain and explore the differences in banking efficiency between the US and European market. The method has similar assumptions as for the ordinary least squares (OLS) regression, along with exogenous variables, normality, zero conditional mean assumption. Furthermore, the outcomes of both the control and treatment group follows parallel trend assumption (Abadie, 2005). We divide between the two markets using a dummy variable to create the control group and the treatment group. The control group is defined as EU companies, while the treatment group consists of U.S banks. Descriptive statistics for the DiD method is displayed in Table 7, and the empirical specification is as follows:

$$Efficiency_{it} = \beta_0 + \beta_1 Location_i + \beta_2 PostCrisis_t + \beta_3\, Location_i PostCrisis_t + \varepsilon_{it} \qquad \text{con } \varepsilon_{it} \sim N(0,\sigma) \tag{9}$$

where:

$$Location_i = \begin{cases} 0\ if\ bank\ is\ American/USA \\ 1\ if\ bank\ is\ European/EU \end{cases}$$

and

$$PostCrisis_t = \begin{cases} 0\ if\ period\ t\ belongs\ to\ the\ PriorCrisis\ Period \\ 1\ if\ period\ t\ belongs\ to\ the\ PostCrisis\ Period \end{cases}$$

$Efficiency_{iT}$ is defined as the level of efficiency given the period T, which is equal to Pre and Post Crisis at location i. PostCrisis is a dummy variable created to differentiation between the period prior to the crisis equal to 0, while the period post crisis is valued at 1. Furthermore, $Location_i$ is the second dummy variable to find the location of the banks prior and post period given by T. The US banks are assigned value 1, while EU banks are at value 0. The third dummy variable, $PostCrisis_T Location_i$ is an interaction variable which is described by both $PostCrisis_T$ and $Location_i$. The variable assigns value 1 to the banks in the US market post crisis, and 0 to the European market. The regression coefficient $\beta_3 PostCrisis_T Location_i$ gauges the treatment effect for the model to explain the

effect of the financial crisis. Lastly, ε_{iT} described the random error of the model. The descriptive statistics shown in table 6 below.

Table 6.

Descriptive Statistics – Difference in Differences

Variable	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*
TE	1952	.628	.269	.03	1
InUS	1952	.574	.495	0	1
PostCrisis	1952	.563	.496	0	1
PostCrisisIntheUS	1952	.323	.468	0	1

InUS: location variable, PostCrisis dummy: 1 = post crisis, 0 = prior crisis, PostCrisisInthe US: interaction variable treatment effect

3.4.1 The Tobit model – Censored regression

The Tobit model is the last of the two methods examining the results from the initial DEA estimation in estimating the relationship between the dependent and the independent variables. The dependent variable is the technical efficiency of each bank over period, while our independent variables are proxies used to measure for size, credit risk, and macroeconomic factors. We follow Doan's et al., (2018) empirical specification:

$$Bank\ Efficiency_{i,t} = \alpha + \beta_1 Bank\ Controls_{i,t} + \beta_3 Credit\ risk_{i,t} + \beta_2 Macro\ Controls_{i,t} + \varepsilon_{i,t} \quad (10)$$

Credit controls

We utilize three variables as proxies for credit controls: Equity (E), Loans to Assets (L/A) and Loan Loss Allowance (LLA) to Assets (Trichet, 2010). Equity is measured by the amount of equity to assets. It indicates the level of capital in bank and its ability to absorb losses incurring in the future, where a good capital ratio ensures the risk is appropriately covered. The L/A ratio used in the estimation indicates greater risk and LLA proxies potential future losses incurred by bad debts. Low levels of LLA banks indicating that banks are exposing themselves more towards bad debts and higher credit risks as shown and elaborately discussed in Jin et al. (2018).

Macro controls

The macroeconomic environment will be controlled against to see if there is a contribution to better efficiency levels with a higher gross domestic product (GDP). GDP is equal to the value that is created by the country`s producers, minus subsidies and including taxes on products. It is the logarithm to gross domestic product per capita, which gives log of the GDP divided by the population.

Size controls

To account for size, we utilize a single variable in accordance with Pasiouras (2008b) where size is denoted by logarithm of the banks total assets. The variable is responsible for controlling for economies of scale which provides an indication as to the impact of the bank`s size on the efficiency score (Doan et al., 2018).

The descriptive statistics by market are shown in table 7 below.

Table 7. Descriptive statistics for EU and USA

	Variable	*Obs.*	*Mean*	*St. Deviation*	*Min.*	*Max.*
Europe	Size	988	11.087	0.846	7.911	12.576
	Equity	988	0.065	0.033	-0.039	0.236
	Loan Loss All.	988	0.005	0.009	-0.005	0.175
	Loans	988	0.553	0.165	0.099	1.103
	GDP per capita	988	4.522	0.099	4.305	4.626
USA	Size	1330	10.277	0.76	7.592	12.419
	Equity	1330	0.108	0.03	0.026	0.404
	Loan Loss All.	1330	0.005	0.056	-0.004	2.024
	Loans	1330	0.644	0.146	0.08	1
	GDP per capita	1330	4.68	0.069	4.56	4.797

4. Empirical Results

Firstly, we present the results from the DEA analysis to track changes in efficiency and serve as a base for the second and third part, which further provides an indication as to how each market has performed in the periods. The second part is based on the results from the difference-in-differences (DID) estimation, where we examine the effects of the financial crisis. The third and final part introduces the results of the Tobit regression to further examine factors behind changes in efficiency based on the two regions and the sets of groups.

4.1 First Stage - DEA results

The estimation on the markets have been run separately for 52 banks in the European Union and 70 banks in the US. From the outcome of the DEA analysis, the efficiency scores are divided into regions and groups based on the lending criteria as set above in table 1, where the focus of the analysis is on VRS as variable return to scale allows for a more fluent comparison between smaller and larger banks. Each group does therefore contain the average results of the banks within that bracket. Following Liu and Ngo (2014), the tables presented show the estimation of the regions and groups based on three time periods which are respectively; 2000-2006, 2007-2010 and 2011-2018, where 2007–2010 is identified as the global financial crisis. The efficiency results of the US and Europe are first presented below in table 8 during the three time periods based on region, and then listed as comparative groups in table 9 that follows further below.

Table 8. Efficiency Results for all layers of analysis

DEA Efficiency Results	(RTE)	**(PTE)**	Scale (S)
Full period			
Full sample	.639	**.758**	.843
US	.718	**.797**	.901
EU	.532	**.705**	.755
Prior			
Full sample	.613	**.721**	.850
US	.726	**.773**	.939
EU	.461	**.651**	.708
During			
Full sample	.646	**.761**	.849
US	.724	**.801**	.904
EU	.542	**.707**	.767
After			
Full sample	.657	**.789**	.833
US	.708	**.816**	.868
EU	.590	**.752**	.785

RTE: Radial Technical Efficiency
PTE: Pure Technical Efficiency
Scale: Scale efficiency

The initial results from the DEA analysis are displayed in Table 8 above based on the two regions in the study. For the full period from 2000–2018, the full sample has efficiency results of 0.758, with scale efficiency coming in at 0.849. EU banks come in with a significantly lower average efficiency, however the numbers do not assess changes and trends. Within the three time periods the average technical efficiency in Europe increased by 16% for the period after the crisis, while the U.S had a more modest increase of 6%. The efficiency levels of the European banks are comparable to other studies over similar time periods. Prior research has found the average efficiency of EU27 banks from 2001–2009 to be 0.72 (Chortareas et al., 2013). However, the authors utilize interest expense rather than deposits and slightly larger outputs given by other earning assets. Furthermore, other research provides estimates close to similar results for the U.S prior to the crisis (1997–2007) at TE = 0.796 using the intermediation approach and almost identical variables (Elyasiani and Wang, 2012). Albeit a positive change in technical efficiency, the U.S scale efficiency is reduced by 7%, while EU banks exhibit a steady increase of 7%. This is an indication of U.S banks producing more outputs, with the current level of input, whereas European banks were able to increase their efforts to operating their optimal size driven by economies of scale. The U.S group still appears to be more overall efficient in contrast to European banks.

Table 9. Comparative Efficiency results for EU and US sample of banks

DEA Efficiency Results US	(RTE)	**(PTE)**	Scale (S)
Full period			
Group 1	0.699	0.797	0.877
Group 2	0.691	0.709	0.975
Group 3	0.777	0.910	0.854
S.I.Bs	0.807	0.970	0.832
Prior			
Group 1	0.691	0.751	0.92
Group 2	0.688	0.701	0.981
Group 3	0.834	0.905	0.922
S.I.Bs	0.848	0.942	0.900
During			
Group 1	0.701	0.800	0.876
Group 2	0.697	0.716	0.973
Group 3	0.788	0.918	0.858
S.I.Bs	0.822	0.965	0.852
After			
Group 1	0.705	0.837	0.842
Group 2	0.691	0.713	0.969
Group 3	0.721	0.910	0.792
S.I.Bs	0.764	0.998	0.766
DEA Efficiency Results EU			
Full period			
Group 1	0.498	0.559	0.891
Group 2	0.440	0.486	0.905
Group 3	0.573	0.755	0.759
S.I.Bs	0.532	0.877	0.607
Prior			
Group 1	0.414	0.482	0.859
Group 2	0.332	0.355	0.935
Group 3	0.518	0.733	0.707
S.I.Bs	0.460	0.821	0.560
During			
Group 1	0.468	0.508	0.921
Group 2	0.424	0.466	0.910
Group 3	0.614	0.778	0.789
S.I.Bs	0.514	0.878	0.585
After			
Group 1	0.587	0.653	0.899
Group 2	0.541	0.610	0.887
Group 3	0.602	0.762	0.790
S.I.Bs	0.604	0.926	0.652

RTE: Radial Technical Efficiency
PTE: Pure Technical Efficiency
Scale: Scale efficiency

Table 9 above shows the efficiency results based on the defined groups in the study. Groups are based on lending volumes (Table 1), and from the results it is clear that S.I.Bs, the largest banks in the study, have the highest technical efficiency in both the U.S and EU for all periods. Interestingly, Group 2 in the EU and US operate at a lower efficiency than Group 1, which has lower overall lending. The gap between the two regions is primarily seen in the difference between groups 1 and 2, where the US operates at respectively at 0.238 and 0.223 points higher than their EU counterpart. European banks across the groups have experienced a clear increase in technical efficiency while groups 2 and 3 in the US show stagnancy despite the crisis. Notable is the difference in scale efficiency *within* the EU and US after the crisis, where the S.I.Bs in the EU are operating at a more optimal scale than in the US. In comparison to the two lower brackets, the large banks are scale inefficient and are not operating at their optimal size. Although the lower brackets operate with high scale efficiency for both regions, before the crisis the average TE (VRS) score of 0.482 for Group 1 in EU would at the frontier only need 48.2% of the current inputs to produce the same levels of output. The 52 banks are outperformed in terms of technical efficiency by U.S banks across all brackets over all three periods, albeit the European groups were able to increase their technical efficiency levels.

4.2 Second stage - Difference in difference (DID)

The second stage of the analysis estimates the impact of the financial crisis on U.S and European banks using the technical efficiency scores obtained from the DEA analysis in the DiD estimation. With US banks as the treatment group and EU banks as control group, the estimation enables for isolation of the financial crisis and its effect on banking efficiency.

Table_10 Linear regression

TE	Coef.	St. Err.	t-value	p-value	95% Conf. interv.		Sig.
Post_Crisis	0.101	0.015	6.81	0.000	0.072	0.131	***
In_The_US	0.122	0.014	8.52	0.000	0.094	0.150	***
Post_Crisis_In_US	-0.058	0.02	-2.96	0.003	-0.097	-0.200	***
Constant	0.651	0.011	59.93	0.000	0.630	0.672	***
Mean depend. Var.		0.757	SD depend. Var.			0.215	
R-squared		0.073	Number of obs.			1830	
F-test		48.119	Prob > F			0	
Akaike Crit. (AIC)		-563.814	Bayesian crit. (BIC)			-541.766	

***p<.01, **p<.05, *p<.1

Table 10 shows that the model is statistically significant at all levels given by the test along with the variables of the model. The time variable Post_Crisis is positive, indicating that the efficiency in the markets have shifted upwards over the periods, which can be seen by the results from the first stage. Both regions show an upward trend in technical efficiency over the periods. The location variables given by *In_the_US* suggest that banks in the US have higher technical efficiency, confirmed in

the previous results. For the majority of the time, U.S banks outperformed their European counterparts. The value of *Post_Crisis_In_US* is equal to the treatment effect, derived from the difference between European and US banks. The negative value shows a negative impact of the financial crisis on technical efficiency.

4.3 Third stage – Tobit estimation

Lastly, we perform OLS and Tobit regressions on the TE results from the initial DEA analysis. With TE (VRS) as the dependant variable, we utilize the regression models to look for the relationship between the independent variables that are size, equity, LLA, Loans and GDP and the dependent variable. The objective of the third stage is to further examine the determinants for change in efficiency between the two regions. The results from the Tobit regression are provided in table 11 that follows below.

Table 11. Third stage Tobit Estimations_Full Period

TE	Obs.	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]		
Size	988	0.217	0.013	16.530	0.000	0.192	0.243	
Equity	988	0.832	0.319	2.610	0.009	0.206	1.459	
LLA	988	-0.923	1.069	-0.860	0.388	-3.020	1.175	
Loans	988	-0.321	0.062	-5.220	0.000	-0.442	-0.201	EU
GDP	988	0.193	0.097	2.000	0.046	0.003	0.384	banks
_cons	988	-2.397	0.417	-5.750	0.000	-3.215	-1.578	
sigma	988	0.274	0.008			0.258	0.289	
Pseudo R2	0.3684							
Prob>Chi2	*0.000*							
694 uncensored obs. - 294 right-censored obs. At TE >=1								
TE	Obs.	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]		
Size	1330	0.160	0.008	20.500	0.000	0.145	0.176	
Equity	1330	0.638	0.177	3.600	0.000	0.290	0.985	
LLA	1330	0.035	0.083	0.420	0.677	-0.128	0.197	
Loans	1330	0.353	0.037	9.560	0.000	0.281	0.426	
GDP	1330	-0.234	0.081	-2.890	0.004	-0.393	-0.075	US
_cons	1330	-0.026	0.348	-0.080	0.940	-0.708	0.656	banks
sigma	1330	0.168	0.004			0.160	0.176	
Pseudo R2	1.898							
Prob>Chi2	*0.000*							
1,033 uncensored obs. - 297 right-censored obs. At TE>=1								

With the Tobit model for Europe and the US in Table 11 we censor TE at maximum = 1 which reduces the sample but according to Doan et al. (2018) further give unbiased results from the coefficient estimation. From the initial Tobit model on European and U.S banks for the full period (2000–2018), we can see all the independent variables are in fact significant, with the exception of LLA and the constant where the model does not find a significant difference for its effect on technical efficiency in the US banks. Furthermore, the results of the OLS regression are presented in Table 12 following, which indicate robust and similar results for the samples above.

Table 12. OLS Estimations_Full Period

TE	Obs.	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]		
Size	988	0.168	0.009	17.960	0.000	0.150	0.187	
Equity	988	0.541	0.231	2.340	0.020	0.087	0.996	
LLA	988	-0.795	0.793	-1.000	0.316	-2.352	0.762	
Loans	988	-0.212	0.045	-4.750	0.000	-0.300	-125	EU
GDP	988	0.167	0.071	2.340	0.019	0.027	0.306	banks
_cons	988	-1.827	0.305	-5.980	0.000	-2.426	-1.228	
R-squared	*0.354*							
Adj. R2	*0.351*							
Prob > F	*0.000*							
TE	Obs.	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]		
Size	1330	0.122	0.006	21.110	0.000	0.111	0.133	
Equity	1330	0.561	0.141	3.960	0.000	0.283	0.838	
LLA	1330	0.019	0.068	0.290	0.775	-0.114	0.153	
Loans	1330	0.356	0.029	12.420	0.000	0.300	0.412	US
GDP	1330	-0.159	0.064	-2.480	0.013	-0.285	-0.033	banks
_cons	1330	-0.003	0.276	-0.010	0.990	-0.546	0.539	
R-squared	*0.276*							
Adj. R2	*0.273*							
Prob > F	*0.000*							

4.3.1 Effect Comparison of the independent variables on the U.S and EU bank

At first glance, the regression model for the banks appear to have a stronger correlation between the independent and dependent variable. For example, in table 12, we can identify some interesting and contrasting results between the two regions where the U.S experiences increases in technical efficiency with a higher loan ratio, while the model finds the opposite for European banks. For GDP, we find that U.S banks can react negatively to an increase, while the EU responds positively.
Following the crisis our models find significant results for the level of assets and loans in both regions. The regions are contrasting where the US could increase technical efficiency with a rise in loans, however European banks could experience a lower efficiency estimate. For the bracketed groups the findings are very widespread. First and foremost, we find that group 1 regardless of region has a different relationship towards the other groups in each of their respective region. When we control for size we find that both U.S and EU banks correlate negatively towards their technical efficiency. In terms of credit risk results are slightly contrasting. The EU banks seem to experience a rise in efficiency with a higher level of loan loss allowance and equity, meaning a decreasing risk. For the U.S counterparts, loan loss allowance is found to be insignificant, while an increase in equity and loans could provide higher technical efficiency. The macro factor seems to have a stronger impact on the smaller banks for both markets. For Group 2 in both the US and EU, we find correlation between higher efficiency results and lower credit risk based on the control variables. The same applies to the third bracket (group 3) in the U.S, however for the European banks in the same group we do not find any significance for loans and equity, but a strong reading for higher efficiency with lower levels of loan loss allowance.

Regarding size, we find that in the U.S banks correlate positively, while the EU has insignificant and negative readings.
The systemically important banks (S.I.Bs), in both markets, display contrasting results to the other groups according to table 13 below. While most of the other groups exhibit higher efficiency levels with lower credit risk, the S.I.Bs in this case would be rewarded for increasing their risk exposure. S.I.B`s also positively correlate with the size of assets. Furthermore, the regions respond differently to GDP per capita as the macro economical factor. S.I.Bs in the US show no significant relationship with GDP levels in the country, while the European banks correlate significantly negatively. This points potentially to structural and regulatory differences between the two regions. Credit provision/circulation within Europe is heavily dependent on macroeconomic fundamentals and channelled largely through banks as opposed to financial markets in the US. Hence the regulators' systemic prominence throughout Europe. Although the individual results from the group regression deviate from the models on the full sample, there are clear indications that in general both regions respond well to increases in size, while decreasing credit risk. However, as the findings show, the S.I.Bs are unique in the sense that an increase in risk exposure could positively increase the technical efficiency of the banks. This goes for Group 3 in Europe as well, while the same group in the U.S would be rewarded with higher efficiency for lower credit risk through higher loans and loan loss allowance. In terms of GDP, the findings are varying but the banks in Group 1 are mostly benefiting from increase in GDP. It is important to point out that the results for the regions have more stable results from the large observations, as S.I.Bs have low observations due to censoring at TE = 1.

Table 13. Third stage Tobit Estimations_Full Period_S.I.Bs

TE	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]		
Size	0.955	0.066	14.510	0.000	0.825	1.085	EU
Equity	-0.846	1.191	-0.710	0.478	-3.196	1.504	
LLA	-12.622	6.255	-2.020	0.045	-24.963	-0.281	
Loans	1.533	0.163	9.400	0.000	1.211	1.854	
GDP	-1.341	0.181	-7.420	0.000	-1.697	-0.984	
_cons	-5.017	0.643	-7.800	0.000	-6.286	-3.748	
/sigma	0.148	0.012			0.124	0.172	
Prob > chi2	0.000						
Pseudo R	0.9525						
86 uncensored obs._104 right-censored observations at TE >= 1							
Size	0.440	0.104	4.220	0.000	0.233	0.646	US
Equity	-5.135	2.064	-2.490	0.014	-9.227	-1.044	
LLA	-16.666	7.336	-2.270	0.025	-31.206	-2.126	
Loans	0.039	0.173	0.220	0.823	-0.304	0.382	
GDP	0.930	0.758	1.230	0.222	-0.572	2.432	
_cons	-7.830	2.942	-2.660	0.009	-13.661	-1.999	
/sigma	0.162	0.032			0.099	0.225	
Prob > chi2	0.000						
Pseudo R	0.7567						
16 uncensored obs._98 right-censored observations at TE >= 1							

U.S. banks appear more technical efficient both before and after the crisis. However, the reason for the difference in efficiency is not necessarily based on the fact that European banks are inferior. In the DiD estimation we find evidence for higher efficiency based on the location of U.S banks. Furthermore, with the Tobit estimation it is clear that the larger banks, experience increase in efficiency with higher credit risk exposure. Hence, regulations of the financial system surrounding the banks could play an important role. There is an ongoing dispute with the implementation of Basel III, where the EU and US sector are yet to be unified in carrying out the regulation. Consequently, parts of the gap could be potentially explained by research findings point to the re-deployment of resources to follow the regulations and increased costs of non-performing loans (Feng and Wang, 2018). It could therefore be reasonable to believe European banks are at a disadvantage against their counterpart in the U.S and are not able to produce the same levels of efficiency unless they were to operate in the same market and under identical regulations.

5. Conclusion

Our findings suggest that U.S banks have been more technical (VRS) and scale efficient than their European counterparts. We also find evidence that systematically important banks (S.I.B) have been significantly more efficient than other tiers regardless of location. The European sector shows lower overall efficiency, yet EU banks have increased their technical efficiency by 16% between the period leading up to the crisis and after while the U.S has increased by only 6%. Based on grouped tiers, the U.S banks outperform European. In terms of scale efficiency, we find a trend where after the crisis European banks operate with higher scale efficiency. Regarding the DiD estimation we check for the impact of the financial crisis. The results from the model indicate that there has in fact been a trend of increased technical efficiency in the sector. U.S banks are found to be more technically efficient over the period, and from the interaction variable we find that the crisis had a negative effect on technical efficiency for the banks in the U.S.

While such results are indeed interesting, they also need to be interpreted cautiously and within the context in which they have been examined. Specifically, there are large structural and regulatory differences between the two markets which also means that, by construction, since two different sets of data are examined these two groups of banks were never compared to the same benchmarks and regardless of the market used as the treatment group. As in Athey and Imbens (2006) in our proposed model, one groups' distribution of unobservables may be different from that of the other group in many and arbitrary ways. Differences thus between the two groups can also be, potentially at least, partially attributed to differences in their conditional distributions.

The Tobit regression examines the factors of change in efficiency. Both European and U.S banks experience higher technical efficiency with increases in assets. For most of the sample a decrease in risk exposure increases technical efficiency, especially with increases in loan loss allowances. In contrast to the general findings of the banks, we do find evidence for S.I.Bs increasing their efficiency with higher credit risk, especially through lower levels of loan loss allowance and equity for U.S banks. This also applies

to group 3 in the EU which shows significant findings for increased efficiency with higher risk.

During the crisis it there is no significant difference for the characteristics in both samples. However, based on the group tiers, EU and U.S banks in the lower brackets can decrease their credit risk and increase efficiency, while S.I.Bs are more restricted with the introduction of Basel III, and new capital requirements. Given the need to boost productivity and enhance profitability in the EU banking sector, these findings suggest that bank consolidation efforts in areas such as rationalisation of branches, digitalisation of business processes and possibly mergers and acquisitions could be intensified.

The outperformance of the US banks is potentially owed to structural and regulatory differences calling for further research. US banks seem to benefit from a more homogeneous domestic market that also includes the globe's greatest investment banking fee pot fund. Contrary to that, the EU has fragmented banking with no truly pan-European banks with the Eurozone banking union project still under construction. Comparatively, owed to the size of the US banking sector as a percentage of the GDP, the US banking sector is much smaller than that of the EU, the price of a regulatory mistake may be relatively less severe for US banks.

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