3. ESTIMATES OF BANK EFFICIENCY IN LUXEMBOURG: A DETAILED ASSESSMENT OF THE DRIVERS ACROSS BUSINESS MODELS

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1. INTRODUCTION

Since the Global Financial Crisis (GFC) 10 years ago, there have been significant changes in the global banking system with implications for bank efficiency. The reasons underlying these changes include the significant losses incurred by European and U.S. banks, the persistent low interest rate environment and newly introduced regulatory elements such as macroprudential policy as well as Basel III. Basel III was implemented in order to make banks more resilient to financial and economic downturns, and macroprudential measures were introduced to help mitigate systemic risk but combined, the increase in regulatory measures may have had an impact on bank efficiency.

In this research, we investigate the efficiency of banks in Luxembourg according to their country of origin as well as their different business models. In the second step, this work investigates the underlying drivers of bank efficiency scores. Luxembourg is an interesting candidate for assessing bank efficiency for numerous reasons. First, Luxembourg is a worldwide financial center and hosts more than 129 banks originating from 27 different countries.[142] Indeed, more than 95 percent of banks operating in Luxembourg come from abroad having parent institutions in Germany, France, Switzerland, Italy and other non-European countries such as China, the U.S. and U.K., to name a few. The banking and financial sector contributed around 25 percent of the country's gross domestic product (GDP) in the third quarter of 2019.[143] In addition, the country is the second largest investment fund center in the world after the U.S. Finally, it is the most important private banking center and the leading center for reinsurance companies in Europe, and the IMF considers Luxembourg as one of the 25 most interconnected economies based on criteria such as the size of the financial sector and connections with financial sectors in other countries.[144] Hence, understanding bank efficiency in terms of different segments such as country of origin as well as business model may have important implications as far as financial stability is concerned in this context of the persistently low interest rate environment. Importantly, studying bank efficiency in a financial centre allows us to reduce potential biases related to the common use of self-reported country data in the sense that it decreases issues related to omitted variables. To the best of our knowledge, this study is the first to investigate bank efficiency in terms of segments and business models in general, and for a financial center, in particular.

One of the challenges in this paper is to measure bank efficiency, which cannot be directly observed. To tackle this issue, we use the nonparametric approach called Data Envelopment Analysis (DEA) to calculate bank efficiency scores. This helps us differentiate our study from the existing literature in the sense that previous research articles mainly used private credit, liquid liabilities or bank assets as measures of financial efficiency and development. However, many researchers including Hasan et al. (2009), Rousseau and Watchel (2011), Diallo (2018) among others have challenged the use of these measures and argued that they only measure the quantity of available funds within the financial sector rather than their quality. The use of the DEA approach also allows us to focus on microeconomic

141 Financial Stability and Macroprudential Surveillance Department, Banque centrale du Luxembourg
142 Revue de Stabilité Financière 2019, Banque Centrale du Luxembourg (BCL).
143 Statistics Luxembourg: https://statistiques.public.lu/fr/economie-finances/index.html
144 The IMF criteria do not reflect a country's broader economic or political importance, and may be periodically re-evaluated as financial sectors develop and their size and connections change over time.

measures of bank efficiency following the intermediation or value added approaches according to input and output variables.

This research uses two avenues for the implementation of the DEA, namely the intermediation and value added approaches. Under the intermediation approach banks play the role of intermediaries as they collect deposits to provide loans. With this approach, we use fixed assets, labor measured by the number of employees, administrative expenses and total deposits as inputs and total loans and non-interest income as outputs. The use of non-interest income as an output is motivated by the fact that the Luxembourg banking sector relies more on fees and commissions as a source of income after the financial crisis. The value added approach assumes that bank liabilities and assets are outputs. Specifically, the categories of both liabilities and assets that have a net contribution in terms of value added according to the external operating costs are considered as outputs. This approach considers a bank as an institution creating income from the difference between earnings from the sale of products and the costs of inputs used in producing these products. For this approach we use fixed assets, labor measured by the number of employees, administrative and interest expenses as inputs and total deposits and loans and non-interest income as outputs following Berger et al. (1987), Berger and Humphrey (1997) and Fethi and Pasiouras (2010). However, using deposits as an output has been challenged by Guarda et al. (2013) who found that deposits are inputs using the directional technology distance function. In this study, we also present the results of efficiency scores using the value added approach. The use of these two approaches in calculating efficiency scores is a novelty and fills a gap in the literature in banking since previous studies mainly followed one approach, namely the intermediation approach.

All data on inputs and outputs come from the Central Bank of Luxembourg (BCL). As this research focuses on bank efficiency in Luxembourg and, most importantly across segments and business models, we use seven geographical segments, namely Luxembourgish, German, French, Swiss, Italian, Chinese and other segments. In terms of business models, we follow the classification of the BCL and the Commission de Surveillance du Secteur Financier (CSSF) in collaboration with the International Monetary Fund (IMF). This classification scheme was used to divide banks into 7 business model segments such as universal, retail and commercial, private, custodian and investment funds, corporate finance and covered bonds banks. In addition, we employ the classification of the Single Supervisory Mechanism (SSM) to classify banks into 3 categories including significant and less significant banking institutions and others. Because the DEA approach assumes certain specifications for returns to scale, this paper uses constant returns to scale (CRS) since this estimator allows for a greater discriminatory power in measuring all banks to the same and optimal level of scale (Curi et al. (2013) and Zelenyuk and Zelenyuk (2015)). The variables in nominal values are converted to real terms using the GDP deflator of Luxembourg with the base year 2010. Our final sample covers 214 banks over the period of 2000-2018, with a total of 2049 bank-year observations available for estimations.

Our results show that the banking sector in Luxembourg has an average efficiency score lying between 0.79 and 0.83 using the intermediation and value added approaches, respectively. This suggests that banks operating in Luxembourg could increase their output by 21 and 17 percent while holding the quantity of inputs constant on average using the intermediation and value added approaches, respectively. We also find that the difference in subsidiary and branch efficiency scores is statistically significant at the 1 percent level using both the intermediation and value added approaches. However, in terms of segments, Luxembourgish banks are found to be the most efficient followed by the German segment. Under the different business models, we find that corporate and retail and commercial banks are the most efficient using both the intermediation and value added approaches. Significant banking institutions have an average score of 0.78, while less significant banking institutions exhibit a score of 0.79 on average. Despite these scores for bank efficiency, it is worth mentioning that average bank efficiency has been decreasing since the GFC but still remains at acceptable level with an average value of 0.8. We also find a statistically significant difference in the means of efficiency scores before and after the global financial crisis at 1 percent level using both the intermediation and value added approaches.

Next, we investigate the micro drivers of bank efficiency in Luxembourg. Our results indicate that there is a positive and significant relationship between bank income diversification and efficiency both measured by the intermediation and value added approaches. We also show that bank concentration measured by the Herfindahl-Hirschmann index (HHI) is positively and significantly related to bank efficiency, rejecting the quiet life hypothesis (QLH). According to bank size, this research establishes the existence of a non-linear relationship between bank size and efficiency, namely an inverted U-shaped relation. In addition, this research finds that equity ratio has a negative and significant effect on bank efficiency, thus validating the agency costs theory. These findings remain robust to potential endogeneity issues such as reverse causality and omitted variables using an instrumental variable (IV) Tobit model. Furthermore, the use of the IV approach confirms the positive effect of bank income diversification on efficiency.

Finally, this research adds several advances to the existing literature. First, it determines efficiency scores for banks operating in a financial centre using both the intermediation and value added approaches. Second, it discusses those scores in terms of business models and segments. Third, it empirically investigates the micro drivers of bank efficiency across business models by tackling the endogeneity issues often present in such empirical exercises. The remainder of this special feature is as follows; section 2 outlines the model and data and section 3 presents the results. Finally, Section 4 discusses and summarizes the findings.

2. MODELS AND DATA

Despite the role played by the banking sector in Luxembourg there have been only a few parametric studies on the efficiency of the banking sector. This research adds to the existing literature by using the nonparametric DEA approach. The DEA is a linear programming based approach that links inputs and outputs of Decision Making Units (DMU) (Charnes et al. (1978) and Charnes et al. (1995)). This approach describes how inputs are used in order to produce outputs across banks. The DEA facilitates the estimation of efficiency scores associated with each bank during a certain period in the first stage. The resulting efficiency scores are analyzed across segments i.e. according to banks countries of origin, branch versus subsidiary; types of banking activities or business models, and implications for financial stability using the Single Supervisory Mechanism (SSM) classification. In the following section, we present the mathematical formalization of the DEA approach following Diallo (2018). We use the output-oriented technique following the literature in bank efficiency. The output-oriented technique solves a linear programming problem to maximize the output of a given bank without adjusting the amount of inputs.[145]

The DEA Model Let n be the sample size of banks. k and o, be inputs and outputs, respectively of bank i. Let $x_i = (x_{i1}, x_{i2}, ..., x_{kj})$ be the vector of inputs of bank i. Let $y_i = (y_{i1}, y_{i2}, ..., y_{oj})$ also be the vector of outputs of bank i. For simplicity, let us assume that the matrix of inputs $k \times n$, and outputs $o \times n$ are respectively given by: $X = (x_1, x_2, ..., x_n)$ and $Y = (y_1, y_2, ..., y_n)$. The linear programming DEA problem of bank i, where (i = 1...n) is:

$$1/Eff_{\mathrm{i}} = \max(\beta_i \geq 1 / xi, yi, X, Y) = \max(\beta_i \geq 1 | \beta_{\mathrm{i}} y_{\mathrm{i}} \leq Y a_i, X a_i \leq x_i, a_i \geq 0, I^t a_i = 1) \quad (1)$$

where α_{i} are non-negative vector of parameters.

145 The output and input-oriented techniques give the same results under constant returns to scale (CRS).

This maximization problem is posed such that a virtual output $Y a_i$ is constructed for each bank *i* according to the weights of outputs of all other banks and then this virtual output is expanded as much as possible under the inputs' constraints of that bank $Xai \geqslant xi$. This virtual output is then compared to the actual output yi. In terms of efficiency, if the output obtained with the maximization problem, namely $Y ai$ is higher than the actual output y_i of bank *i*, then the bank is inefficient, otherwise the bank is located at the efficient frontier.

It is very important to choose the right specification for returns to scale. In their seminal paper, Charnes et al. (1978) first proposed a DEA linear programming technique using the input-oriented method combined with constant returns to scale (CRS). Notwithstanding, in 1984, Banker et al. (1984) introduced a model using variable returns to scale (VRS). Since then there has been significant debate among academics regarding the use of CRS and VRS in banking. Particularly, McAllister and McManus (1993), Wheelock and Wilson (2001), Hughes et al. (2001), Feng and Seritilis (2010), and Wheelock and Wilson (2012) all found that banks operate under increasing returns to scale for the U.S. banking sector. For example, according to Tim Coelli (2008) the use of the CRS should only be considered when all decision DMUs (i.e. banks in our case) are operating at an optimal scale. In this research, we use CRS since it allows for more discriminatory power across all banks in terms of the level of scale.

Econometric Model

To estimate the determinants of bank efficiency, we use the panel random-effects Tobit model, which imposes an upper limit of 1 on the efficiency scores obtained during the first stage. In doing so, the following econometric model is estimated:

$$\text{Efficiency}_{it} = X_{it}\beta + v_i + \theta_j + \rho_t + E_{it} \qquad (2)$$

where *i* and *t* denote bank and year, respectively. X_{it} are the determinants of bank efficiency, consisting of capital and equity ratios, diversification, size and concentration. We also add bank, country of origin and year fixed-effects captured by v_i, θ_j and ρ_t, respectively. Eit is the error term.

Data

We use annual bank data obtained from the Central Bank of Luxembourg (BCL) for the period 2000-2018. Under the intermediation approach we use fixed assets consisting of the sum of property, equipment and investment property, labor measured by the number of employees, administrative expenses and total deposits defined as the sum of interbank and customer deposits as inputs and total loans consisting of interbank and customer loans and non-interest income such as net fees and commissions, foreign exchange and dividend income and other income as outputs. For the value added approach, we use fixed assets, labor, administrative and interest expenses as inputs and total deposits and loans and non-interest income as outputs. The variables in nominal values are converted to real terms using the GDP deflator of Luxembourg with the base year 2010. The final sample is an unbalanced panel and covers 2049 bank-year observations. Below we present some descriptive statistics of the input and output variables.

3. RESULTS

3.1 EFFICIENCY SCORES

The results obtained from the intermediation approach are displayed in Table 1. For our sample of 2049 bank-year observations, including branches and subsidiaries with all types of business models, the average bank efficiency in Luxembourg between 2000-2018 amounted to 0.79, with a standard deviation of 0.059. This suggests that banks in Luxembourg operating under this approach could increase their level of output by 21 percent on average while holding the quantity of inputs constant. In addition, the results suggest that the mean bank efficiency was equal to 0.78 and 0.82 for banks with subsidiaries and branches, respectively. Using segments, specifically classification according to a bank's country of origin, we find that Luxembourgish banks are the most efficient followed by German and Chinese banks. The least efficient banks are found to be French and Swiss banks. However, the efficiency scores of Chinese banks should be interpreted with caution since Chinese banks are predominantly corporate banking institutions. Using the business models classification, we find that corporate, custodian and retail and commercial banks are the most efficient with a score of 0.83 and 0.81 on average, respectively. In terms of financial stability based on SI versus LSI classification, significant and less significant banking institutions have efficiency scores of 0.78 and 0.79 on average, respectively.

Table 1:

Bank Efficiency Scores–Intermediation Approach

VARIABLES	OBS	MEAN	STD. DEV.	MIN.	MAX.
Average bank efficiency (Luxembourg)	2,049	0.788	0.059	0.570	1
Banks with subsidiaries	1,818	0.785	0.053	0.570	1
Banks with branches	231	0.818	0.088	0.601	1
Luxembourgish segment	88	0.835	0.080	0.719	1
German segment	214	0.804	0.068	0.601	1
French segment	175	0.779	0.040	0.723	0.997
Swiss segment	159	0.783	0.049	0.570	1
Italian segment	94	0.799	0.052	0.672	1
Chinese segment	77	0.801	0.079	0.618	1
Other segment	1,242	0.783	0.055	0.584	1
Universal banks	74	0.762	0.014	0.731	0.800
Retail and commercial banks	116	0.811	0.074	0.645	1
Custodian banks and IF activities	314	0.781	0.054	0.602	1
Private banks	663	0.780	0.044	0.570	1
Corporate finance banks	222	0.828	0.083	0.607	1
Covered bonds banks	23	0.805	0.060	0.690	1
Other	637	0.786	0.057	0.584	1
Significant banking institutions	518	0.784	0.044	0.653	1
Less significant banking institutions	585	0.790	0.061	0.570	1
Other	946	0.790	0.064	0.584	1

Source: BCL

Table 2 displays the descriptive statistics of efficiency scores using the value added approach. The average level of bank efficiency in Luxembourg over the period of 2000-2018 was estimated at 0.83 with a standard deviation of 0.062. This suggests that under this approach banks could increase their output by 17 percent while holding the quantity of inputs constant on average. In terms of subsidiary versus branch banks, we find that the averages efficiency scores are equal to 0.82 and 0.87, respectively. The interpretation of findings obtained for segments, business models and financial stability are similar to those obtained via the intermediation approach. Figure 1 shows the evolution of bank efficiency scores using both the intermediation and value added approaches over the period 2000-2018 for the Luxembourg banking sector.

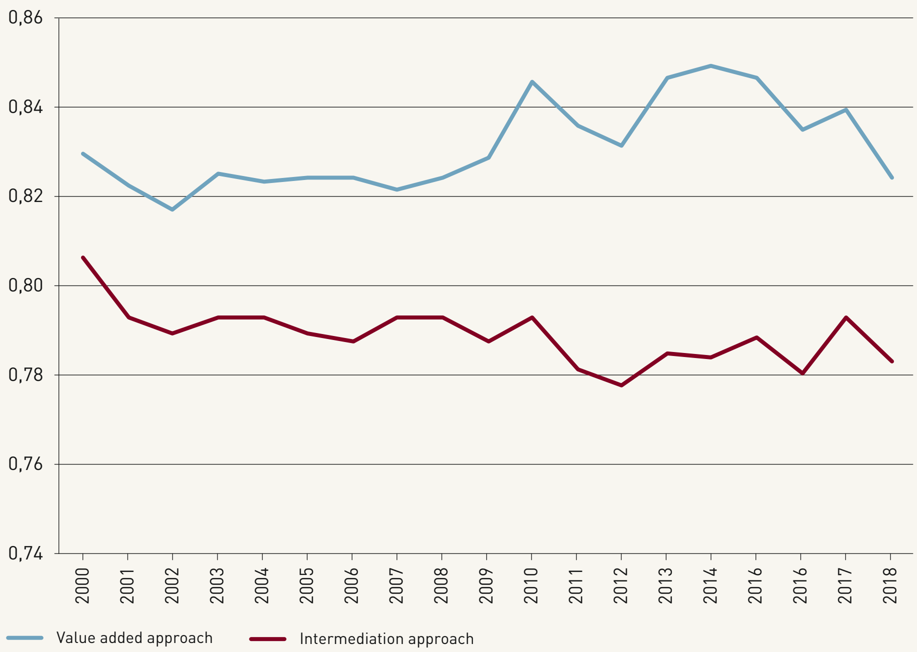
Table 2:

Bank Efficiency Scores–Value Added Approach

VARIABLES	OBS	MEAN	STD. DEV.	MIN.	MAX.
Average bank efficiency (Luxembourg)	2,049	0.831	0.062	0.543	1
Banks with subsidiaries	1,818	0.825	0.056	0.543	1
Banks with branches	231	0.874	0.082	0.696	1
Luxembourgish segment	88	0.866	0.075	0.767	1
German segment	214	0.851	0.067	0.696	1
French segment	175	0.818	0.046	0.752	1
Swiss segment	159	0.823	0.047	0.676	1
Italian segment	94	0.854	0.051	0.696	1
Chinese segment	77	0.842	0.062	0.754	1
Other segment	1,242	0.825	0.062	0.543	1
Universal banks	74	0.795	0.016	0.754	0.832
Retail and commercial banks	116	0.852	0.083	0.668	1
Custodian banks and IF activities	314	0.852	0.058	0.737	1
Private banks	663	0.821	0.049	0.676	1
Corporate finance banks	222	0.853	0.085	0.543	1
Covered bonds banks	23	0.834	0.055	0.719	0.968
Other	637	0.823	0.059	0.591	1
Significant banking institutions	518	0.826	0.048	0.696	1
Less significant banking institutions	585	0.835	0.067	0.543	1
Other	946	0.831	0.065	0.591	1

Source: BCL

Figure 1
Banking Efficiency Scores in Luxembourg



Source: BCL

In order to test the independence of the two samples of efficiency estimates, we perform the mean-comparison test and we find that the efficiency scores of subsidiary and branch banks are statistically different from each other, on average, at the 1 percent level for both the value added and intermediation approaches. This finding is in contradiction with those of Aly et al. (1990) who showed that there is no difference in the distribution of efficiency estimates for branches versus non-branch banks in the United States. This result is, however, in line with Curi et al. (2013) for Luxembourg. In terms of efficiency in both the pre- and post-financial crisis periods (i.e. before and after 2007), we find a statistically significant difference in the means of efficiency scores before (p-value=0.0091) and after (p-value=0.000) the crisis using the intermediation and value added approaches, respectively.

3.2 DRIVERS OF BANK EFFICIENCY

Table 3 presents the descriptive statistics of the variables used to investigate the main drivers of bank efficiency in Luxembourg. Recall that capital and equity ratios are expressed in terms of total assets. Bank diversification is measured by the ratio between non-interest income and total assets. Size is the logarithm of total assets and concentration is the measure of a bank's market power in terms of total assets obtained using the Herfindahl-Hirschmann index (HHI).

Table 3:
Summary statistics–Determinants of Bank Efficiency

VARIABLES	OBS	MEAN	STD. DEV.	MIN.	MAX.
Efficiency (Intermediation)	2,049	0.788	0.059	0.570	1
Efficiency (Value added)	2,049	0.831	0.062	0.543	1
Capital ratio	2,049	0.064	0.187	0	3.078
Equity ratio	1,933	0.091	0.121	-0.523	1.172
Diversification	2,042	0.020	0.041	0.0000119	0.7252
Size	2,042	16.649	1.714	10.410	20.636
$(\text{Size})^2$	2,042	280.148	57.073	108.380	425.868
HHI assets	2,049	0.165	0.301	0	1

Source: BCL

We present results in Table 4 using bank efficiency scores calculated under the intermediation approach as the dependent variable. In column (1) of this Table, we regress the determinants, namely capital and equity ratios, diversification, size and its square and concentration on bank efficiency for all banks in the sample. We find a positive and significant relationship between income diversification and efficiency at the 1 percent level. The coefficients associated with size and its square are positive and negative, respectively. Both estimated coefficients are significantly different from zero at the 1 percent level. This result suggests the existence of a nonlinear relation between bank size and efficiency. Moreover, it suggests that there is an inverted-U shaped relationship between size and efficiency in Luxembourg, reconciling both views on the impact of bank size on efficiency. Using the HHI index as measure of bank concentration, we are also able to reject the quiet life hypothesis (QLH) for banks operating in Luxembourg since its coefficient is positive and significantly different from zero at the 1 percent level. In columns (2)-(5) of Table 4, we look at the determinants of bank efficiency by considering different types of business models in the Luxembourg banking sector. Column (2) estimates the same model for universal banks and shows that bank income diversification is positively and significantly related to efficiency at the 1 percent level and the magnitude of its coefficient increases sharply. However, bank efficiency is negatively and significantly associated with equity ratio. In addition, the inverted U-shaped relationship between size and efficiency is confirmed for this type of banking business model. Column (3) focuses on retail and commercial banks, the coefficient of diversification remains positive but becomes insignificant. Moreover, the QLH is also rejected for this type of banking activity. Column (4), shows the results for private banks and confirms the fact that diversification and concentration remain positive and significant at the 1 level, respectively. For private banking, the nonlinear relationship between size and efficiency remains robust. Interestingly, the coefficient associated with the capital ratio enters positively and significantly different from zero at the 5 percent level, while the equity ratio is found to be negatively and significantly related to bank efficiency at the 5 percent level. Finally, columns (5) and (6) show the results for custodian and investment fund banks, and corporate banks, respectively. For these banks, the coefficient of bank income diversification remains positive and significant at the 1 percent level, supporting the positive association between diversification and efficiency. These findings are suggestive of the strong positive impact of bank income diversification on efficiency across banks and business models in Luxembourg.

Table 4:

Determinants Bank Efficiency–Intermediation Approach

	ALL BANKS	UB	RCB	PB	CIFB	CFB
Capital ratio	0.0075	0.0037	0.0811	0.0194**	0.0037	0.0128
	(0.0073)	(0.0103)	(0.1378)	(0.0087)	(0.0215)	(0.0188)
Equity ratio	-0.0130	-0.1148***	-0.0557	-0.0526**	0.1478***	-0.0351
	(0.0172)	(0.0203)	(0.0920)	(0.0252)	(0.0410)	(0.0486)
Diversification	0.4306***	3.2070***	0.1117	0.7026***	0.2865***	1.4178***
	(0.0409)	(0.1788)	(0.7319)	(0.0917)	(0.0478)	(0.3871)
size	0.0747***	0.3583**	0.3644***	0.1233***	0.0071	0.0521
	(0.0198)	(0.1619)	(0.1290)	(0.0304)	(0.0349)	(0.0690)
$(size)^2$	-0.0016***	-0.0085**	-0.0112***	-0.0030***	0.0001	-0.0008
	(0.0006)	(0.0041)	(0.0043)	(0.0009)	(0.0011)	(0.0020)
HHI assets	0.0165***	0.1124	0.0622***	0.0163*	0.0174	0.0215
	(0.0059)	(0.1241)	(0.0184)	(0.0085)	(0.0111)	(0.0191)
Country of origin fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	1391	74	116	644	301	200
Number of groups	114	4	11	43	26	24
Number of right-censored observations	14	0	2	2	3	6
Log likelihood	2633.708	292.859	220.527	1390.872	585.034	305.690
χ^2	2231.058	624.389	445.531	968.879	321.934	394.911

*Source: BCL. Note that (***, ** and *) indicate significance at the 1%, 5% and 10% levels, respectively. All regressions contain the constant coefficient. Standard errors are in parenthesis. UB, RCB, PB, CIFB and CFB, respectively stand for Universal, Retail and Commercial, Private, Custodian and Investment Funds and Corporate Finance Banking.*

In Table 5, we use bank efficiency measured by the value added approach as dependent variable. Column (1) considers all banks and shows positive and significant relationships between diversification, concentration and bank efficiency at the 1 percent level. However, the coefficients associated with bank size and its square are not significant. Interestingly, the equity ratio enters negatively and significantly different from zero at the 1 percent level, suggesting that a higher level of equity decreases efficiency. This finding may be related to the agency costs theory developed by Jensen and Meckling (1976). Moreover, this theory argues that equity financing increases the agency costs between equity-holders and managers of banks because of their diverging objectives. The results for universal banks in column (2) indicate positive and significant relationships between banks' capital ratios and diversification at the 5 and 1 percent levels, respectively. Column (3) focuses on retail and commercial banks. The results show that the coefficients associated with size and concentration all enter positively and significantly different from zero at the 1 percent level, respectively. The square of bank size also enters negatively and is significantly different from zero at the 1 percent level. This evidence suggests the presence of an inverted U-shaped relation between size and efficiency for retail and commercial banks. The equity ratio and diversification are found to be negatively and significantly associated with efficiency at the 5 and 1 percent levels, respectively. This negative relationship between income diversification and efficiency may suggest that diversification has a negative impact on the efficiency of retail and commercial banks. Using private banks in column (4), the coefficients for income diversification and concentration remain positive and significant at the 1 percent level, thus rejecting the QLH. The same findings emerge for corporate finance banking in column (6). However, for custodian and investment fund banks, none of the determinants of bank efficiency are found to be significant as shown in column (5).

Table 5:

Determinants Bank Efficiency–Value Added Approach

	ALL BANKS	UB	RCB	PB	CIFB	CFB
Capital ratio	0.0095	0.0286**	0.1771	0.0151	-0.0102	0.0180
	(0.0072)	(0.0133)	(0.1397)	(0.0096)	(0.0178)	(0.0155)
Equity ratio	-0.0454***	-0.0420	-0.1586*	-0.0691**	0.0371	-0.0034
	(0.0167)	(0.0261)	(0.0926)	(0.0277)	(0.0343)	(0.0398)
Diversification	0.1059***	2.4202***	-2.6255***	0.4318***	-0.0260	0.8722***
	(0.0404)	(0.2302)	(0.7417)	(0.1007)	(0.0406)	(0.3196)
Size	0.0008	0.2450	0.3885***	0.0252	-0.0086	0.0868
	(0.0198)	(0.2084)	(0.1298)	(0.0334)	(0.0329)	(0.0562)
$(\text{Size})^2$	0.0003	-0.0057	-0.0127***	-0.0003	0.0001	-0.0019
	(0.0006)	(0.0053)	(0.0043)	(0.0010)	(0.0010)	(0.0016)
HHI assets	0.0216***	-0.0055	0.0726***	0.0334***	-0.0004	0.0481***
	(0.0057)	(0.1598)	(0.0189)	(0.0093)	(0.0091)	(0.0156)
Country of origin fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	1391	74	116	644	301	200
Number of groups	114	4	11	43	26	24
Number of right-censored observations	37	0	5	6	13	13
Log likelihood	2615.213	274.176	211.363	1315.159	615.184	329.659
x^2	3106.954	495.128	587.754	1083.646	918.651	671.976

*Source: BCL. Note that (***, ** and *) indicate significance at the 1%, 5% and 10% levels, respectively. All regressions contain the constant coefficient. Standard errors are in parenthesis. UB, RCB, PB, CIFB and CFB, respectively stand for Universal, Retail and Commercial, Private, Custodian and Investment Funds and Corporate Finance Banking.*

3.3 Instrumental variable (IV) estimation and causal relationships

The use of the Tobit IV method allows us to deal with endogeneity problems in terms of reverse causality between our determinants i.e. capital and equity ratios, diversification, size and con- centration, and bank efficiency as well as omitted variables issues. This endogeneity between capital, equity, diversification, size and concentration has been extensively discussed in the literature (Berger and Bonaccorsi di Patti (2006), Altunbas (2007), Laeven and Levine (2007) and Fiordelisi et al. (2011) among others). For example, if bank efficiency affects the choice of capital structure in terms of leverage, then failure to take this reverse causality into account may result in simultaneous equations bias. In addition, as financial institutions choose to diversify or not to diversify, the same bank level characteristics that guide this decision may also impact bank efficiency, which may lead to omitted variables issues. Finally, more efficient banks seem to eventually become better capitalized, tend to increase their market share and hence, become larger financial institutions.

Instruments

Finding good instruments that satisfy both the independence assumption and exclusion restriction for a causal inference can be a challenging task in applied econometrics. In this paper, the instruments we use are the first and second lagged variables of banks capital and equity ratios, diversification, size and its square, and concentration in the spirit of Blundell and Bond (1998, 2000). Recently, Reed (2015) motivated the use of lagged variables as instruments instead of using them as controls if there is no serial correlation. The main idea is that the first and second lagged variables of capital and equity ratios, diversification, size and its square and concentration precede the real variables and the causality goes from the lagged variables to the real ones. This technique allows us to establish a causal relationship between our drivers and bank efficiency.

Table 6 re-estimates the model using the IV approach and intermediation method in selecting inputs and outputs. When all banks are considered in our sample, we find that income diversification has a positive and significant effect on bank efficiency at the 1 percent level, and there is an inverted U-shaped causal relationship between bank size and efficiency. These findings validate the results obtained with the panel Tobit model. However, the use of the IV approach renders the coefficient of concentration insignificant. This suggests that there is no clear evidence in favour of an impact of bank concentration on efficiency also known as the QLH. Moreover, the negative and significant effect of equity ratio on bank efficiency remains altered, thus confirming the agency costs theory. Using universal banks in column (2), the result related to diversification remains unaltered. For retail and commercial banks in column (3), the capital ratio also enters positively and significantly different from zero at the 5 percent level. However, bank income diversification becomes insignificant. Interestingly, the QLH is not rejected for this business model as the coefficient associated with bank concentration enters negatively and significantly different from zero at the 10 percent level. For private and custodian banks in columns (4) and (5), diversification and size seem to play an important role in enhancing bank efficiency.

Table 6:

IV Method–Intermediation Approach

	ALL BANKS	UB	RCB	PB	CIFB	CFB
Capital ratio	-0.0005	-0.0573	0.4761**	0.0183	-0.0446*	0.0257
	(0.0109)	(0.0367)	(0.2090)	(0.0120)	(0.0254)	(0.0468)
Equity ratio	-0.0602*	-0.1067**	-0.0866	-0.0934**	-0.0229	-0.0513
	(0.0322)	(0.0525)	(0.1459)	(0.0369)	(0.0770)	(0.1410)
Diversification	0.3376***	3.0128***	-0.8386	0.6545***	0.0611	1.4006
	(0.0689)	(0.4038)	(0.8002)	(0.2249)	(0.0836)	(1.1463)
Size	0.0898***	0.4157	0.1960	0.1330***	0.0756	-0.0212
	(0.0303)	(0.4258)	(0.1748)	(0.0441)	(0.0467)	(0.1761)
$(Size)^2$	-0.0021**	-0.0099	-0.0057	-0.0032**	-0.0025*	0.0012
	(0.0009)	(0.0108)	(0.0055)	(0.0013)	(0.0014)	(0.0050)
HHI assets	-0.0335	0.1986	-0.4071*	0.0107	-0.1507*	-0.0898
	(0.0417)	(0.3411)	(0.2342)	(0.0469)	(0.0822)	(0.1308)
Country of origin fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	1073	62	75	532	237	131
x^2	2399.313	216.425	660.427	1124.67	333.140	295.274

*Source: BCL. Note that (***, ** and *) indicate significance at the 1%, 5% and 10% levels, respectively. All regressions contain the constant coefficient. Standard errors are in parenthesis. UB, RCB, PB, CIFB and CFB, respectively stand for Universal, Retail and Commercial, Private, Custodian and Investment Funds and Corporate Finance Banking. The instruments are the first and second lag of capital and equity ratios, diversification, size and its square, and concentration.*

Finally, Table 7 uses the IV method and value added approach for bank efficiency. The results are quite similar to those obtained previously, namely the positive and significant effect of bank income diversification on efficiency for all banks and business models exception for retail and commercial banks. In addition, the equity ratio has also a negative and significant impact on bank efficiency for retail and commercial, and private banks.

Table 7:

Instrumental Variable Method: Determinants Bank Efficiency–Value Added Approach

	ALL BANKS	UB	RCB	PB	CIFB	CFB
Capital ratio	0.0024	0.0172	0.9003***	0.0137	-0.0324	0.0428
	(0.0110)	(0.0339)	(0.2667)	(0.0134)	(0.0253)	(0.0349)
Equity ratio	-0.0598*	-0.0283	-0.4207**	-0.1094***	0.0254	-0.0802
	(0.0326)	(0.0485)	(0.1843)	(0.0411)	(0.0772)	(0.1054)
Diversification	0.2330***	2.2159***	-3.2534***	0.8645***	0.1938**	1.1531
	(0.0706)	(0.3728)	(1.0075)	(0.2505)	(0.0981)	(0.8699)
Size	-0.0117	0.7009*	0.3532	0.0415	0.0113	-0.1161
	(0.0339)	(0.3932)	(0.2200)	(0.0491)	(0.0639)	(0.1311)
$(Size)^2$	0.0006	-0.0173*	-0.0112	-0.0007	-0.0003	0.0037
	(0.0010)	(0.0100)	(0.0070)	(0.0014)	(0.0019)	(0.0037)
HHI assets	-0.0269	-0.1550	-0.2824	-0.0578	0.0910	0.0364
	(0.0419)	(0.3149)	(0.2949)	(0.0522)	(0.0912)	(0.0973)
Country of origin fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	1073	62	75	532	237	131
x^2	3205.958	351.292	642.445	1249.751	709.077	637.530

*Source: BCL. Note that (***, ** and *) indicate significance at the 1%, 5% and 10% levels, respectively. All regressions contain the constant coefficient. Standard errors are in parenthesis. UB, RCB, PB, CIFB and CFB, respectively stand for Universal, Retail and Commercial, Private, Custodian and Investment Funds and Corporate Finance Banking. The instruments are the first and second lag of capital and equity ratios, diversification, size and its square, and concentration.*

4. CONCLUSION

According to our findings using both the intermediation and value added approaches, we show that corporate finance, retail, and commercial banks are the most efficient banks in Luxembourg, followed by custodian and investment funds and private banks. These findings may be explained by the revenue and cost structures of banks' business models. According to the BCL's 2019 Financial Stability Review, interest income represents more than 78 percent of retail and commercial banks revenues. A similar observation is also found for corporate finance banks with 69 percent of their income coming from interest-related income. However, different results emerged for custodian and investment funds and private banks. More precisely, non-interest income such as net fees and commissions represent the largest share of their incomes with 75 and 49 percent for custodian and private banks, respectively. In view of the persistently low interest rate environment, we looked at bank efficiency scores of banks deriving their revenues from interest-related activities, namely retail and commercial, and corporate finance banks before and after the Global Financial Crisis (GFC). Our results did not indicate any statistical differences in relation to efficiency estimates for these banks before and after the GFC using both the intermediation and value added approaches as we found *p-values* of 0.56 and 0.26, respectively. In order to delve into these findings, we assess the drivers and other factors underlying bank efficiency scores in Luxembourg. More precisely, this study conducts an empirical investigation to analyze the main determinants of bank efficiency across business models. Using the instrumental variable approach for causal inference, we find the following results. For retail and commercial banks, the coefficient associated with the capital ratio in terms of total assets is positive and significant; suggesting that better capitalization enhances efficiency for this particular business model. This finding is in line with the literature in banking, which argues that banks holding more capital are more likely to be well managed and more profitable financial institutions, hence more efficient compared to those with less capital. For private and custodian and investment banks, size has a nonlinear impact on bank efficiency, namely an inverted U-shaped relationship between size and efficiency. Interestingly, we show that diversification has a positive and significant effect on efficiency for all banks across business models exception for retail and commercial banks.

To conclude, this research used the Data Envelopment Analysis (DEA) method to estimate bank efficiency in Luxembourg, which is an international financial center. Using data from 2000-2018, this study finds that the Luxembourg banking sector has an average efficiency score lying between 0.79 and 0.83 using the intermediation and value added approaches, respectively. According to segments, i.e. countries of origin, this work also shows that Luxembourgish banks are the most efficient, while corporate banks are found to be the most efficient in terms of their business models. In addition, the levels of bank efficiency for significant and less significant banking institutions are similar on average. However, bank efficiency scores in Luxembourg have been decreasing since the Global Financial Crisis (GFC). Precisely, we find a statistically significant difference in the means of efficiency scores before and after the crisis at the 1 percent level for both the intermediation and value added approaches.

Looking ahead, the results obtained in this paper may have important policy implications. First, this research has clearly shown the positive effect of bank income diversification on efficiency for banks according their type of activity. This result is in line with the ECB's November 2019 Financial Stability Review , which found that the low profitability of the euro area banking sector can be mainly attributed to the limited degree of revenue diversification since 2012. Second, it found an inverted U-shaped causal relationship between size and efficiency, suggesting there is a nonlinear relationship between bank size and efficiency. Third, the equity ratio has a negative and significant effect on bank efficiency, in line with the agency costs theory developed by Jensen and Meckling (1976). Hence, our results suggest that banks operating in Luxembourg could diversify their activities/revenues in order to increase efficiency. Additionally, financial regulators could monitor banks in terms of size and the equity ratio in order to enhance bank efficiency. Third, there was no clear evidence between bank concentration and efficiency as suggested by the quiet life hypothesis (QLH). The drivers identified in this research provide some insight into how banks in Luxembourg may potentially increase their efficiency.

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