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Master Thesis - Msc Economometrics and Management Science (Quantitative Finance)

Factors determining bank net interest margins in EU15

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Abstract

The main aim of this paper is to determine the key factors that affect the net interest margin of banks in the European banking industry and to what extent. Based on the existing literature, the effect of certain bank-, industry- and country-specific variables is estimated on a sample of 426 banks from 15 European countries over the sample period 2013-17. Owing to the highly persistent nature of bank profitability, a dynamic panel data model is estimated using system-GMM as developed by Blundell and Bond (1998). The results suggest that internal factors such as size of the bank, cost efficiency as well as how diversified its activities are, have a strong negative impact on bank net interest margin. Thus, in today's era of digitalisation it is crucial for banks to be more cost-efficient by means of online banking and well diversified into non-traditional interest bearing activities, in order to remain profitable.

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1 Introduction

In light of the recent financial crisis, European banks have not been able to match the pace of recovery of their American counterparts. While the US economy has largely benefitted from an interventionist style of policy-making supported by tax cuts and a positive economic growth, the same is not true for the European economy (Lakhani et al., 2019). Several factors can be identified that prevent European banks from being persistently profitable: an environment of low sometimes negative interest rates penalises banks with excess deposit reserves in an attempt to stimulate credit availability in the economy, implementation of a rigid regulatory and supervisory framework namely the the Single Supervisory Mechanism and Single Resolution Mechanism, as well as the Banking Resolution and Recovery Directive, and lastly lack of a coherent banking system across Europe. High costs of operation coupled with the aforementioned factors have handicapped the development of a profitable banking industry thereby hampering the overall growth and productivity of the European economy.

The last two decades have witnessed a surge in globalisation, market integration as well as technological and structural changes across the globe; the European banking industry being no exception. Banks operating in a unified market can potentially benefit from cross-country diversification reducing their exposure to cyclical risk in the domestic economy.[1] However, on the flip side the harmony in an integrated economy can possibly eliminate the advantage of operating on foreign land. Banks have adequately responded to the prevalent competition in the industry by growing beyond borders as well as expanding their scope and scale of services. Furthermore, banks have also diversified into non-interest generating activities such as fee-based and trading activities besides their principal function of mobilising the economy's savings.

An important implication of global financial integration is the presence of foreign banks in domestic markets. Foreign bank entry offers multi-fold benefits for the host economy. Foreign banks stimulate a competitive banking environment forcing domestic banks to diversify and improve the quality of intermediation services as well as to lower their administrative costs. [2] This is often accompanied by a technological spillover ultimately improving managerial as well as operational efficiency in the domestic banking sector. All in all, it helps to promote economic growth and financial stability in the host country.

Irrespective of their ownership structure, all banks aim at improving their profitability which is quantified by various measures. One such measure is the net interest margin (NIM)

[1] https://www.ecb.europa.eu/press/key/date/2019/html/ecb.sp190625~6d33411cff.en.html

[2] https://iems.ust.hk/tlb4

of banks: it measures the difference between the interest received by banks on loans and the interest paid by thme on deposits, adjusted relative to the amount of interest generating assets. NIM depicts the price charged by banks to cover their cost of intermediation. A majority of studies conducted on NIM are based on the seminal dealership model developed by (Ho and Saunders, 1981). The authors model the bank as a risk-averse dealer that sets the interest rates to balance the asymmetrical arrival of loan demands and deposit supplies while maximising the expected utility of its terminal wealth. Profitability of banks are subject to internal factors which are controlled by the bank management as well as external macro factors that are independent of the decisions made by the bank management but impact the overall economic environment in which the banks operate.

The aim of this paper is to determine which of the internal factors (bank-specific) and external factors (industry- and country-specific) significantly affect the NIM of foreign and domestic banks in EU15 (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden, United Kingdom) and to what extent. The interdependence of a stable financial system and economic growth makes this study relevant not only for the management of the banks but also the regulatory and supervisory bodies as well as policymakers. The results obtained can potentially be used to design macro policies aimed at achieving a stable economic environment on the one hand and to take sound managerial decisions to provide an efficient intermediation service, on the other.

The remainder of the paper is organised as follows. Section 2 broadly reviews the works of previous authors in determining the factors affecting bank NIM in the US as well as various European countries. Additionally, it also describes the results obtained from studies conducted with regard to domestic and foreign banks in countries like Australia as well as the European banking industry. Next, section 3 gives a detailed description of the dependent as well as the independent (bank-, industry- and country-specific) variables as well as a review of the results obtained by previous researchers for that variable. Section 4 describes the sample of banks used in the current research, sub-divided on bank-type and ownership, as well as the source of the data obtained. It is followed by section 5 which describes the principal method of estimation employed by the researcher which is system generalised method of moments (system-GMM). Next, section 6 describes how the dependent variable is affected by each of the explanatory variables in isolation. This brings the readers to section 7 which presents the key findings obtained by the researcher. The researcher attempts to evaluate the performance of the system-GMM estimates by estimating simulated data using the same method. The

design and results of the simulation process is described in section 8. Lastly, sections 9 and 10 conclude the paper as with a discussion of the main findings and scope for future research.

2 Literature Review

A majority of the previous studies are based on the seminal bank-dealership model developed by (Ho and Saunders, 1981). With the help of a cross-sectional regression followed by a time series regression, the authors concluded that a positive interest margin would exist so long as there is a mismatch in the supply of deposits and demand for loans. Various studies in the future extended the dealership model to include heterogeneous loans and deposits (Allen, 1988), changed the source of uncertainty from deposit and loan rates to the instantaneous money-market (McShane and Sharpe, 1985) and include default risk along with its interaction with interest rate risk (Angbazo, 1997). The study of Saunders and Schumacher (2000) applies the model of Ho and Saunders (1981) to a multicountry setting (US and Europe) over a period of 1988-1995. Their main findings suggest that the bank net interest margins react positively to a segmented and restricted market structure as well as a volatile interest rate environment. More recently Maudos and de Guevara (2004) extended the dealership model to include operating costs as well as a direct measure of market power to determine the interest margins of commercial banks. They concluded that the upward pressure exerted by a concentrated market on NIM is countered by a stable credit and interest risk environment and reduced operating costs.

Several studies on individual countries such as USA, Malaysia, Tuninsia, Greece, Switzerland, China, etc. (Angbazo, 1997; Guru et al., 1999; Naceur, 2003; P.Athanasoglou et al., 2008; Dietrich and Wanzenried, 2011; Sufian and Habibullah, 2009) have identified factors such as default and interest-risk premium, operational efficiency, capital strength, size, market power and liquidity which affect bank NIM. Additionally, NIM of European banks has also been an interesting area of research in the past two decades (Demirguc-Kunt and Huizinga, 1999; Staikouras and Wood, 2003; Goddard et al., 2004; Valverde and Fernandez, 2007; Athanasoglou et al., 2008; Lepetit et al., 2008b). Molyneux and Thornton (1992) were among the first researchers to study the bank performance in eighteen European countries over the period 1986-1989. Their results suggested that bank concentration, nominal interest rates as well as state-ownership positively affected the return on capital. Both the groups of the above mentioned studies have identified a few common internal and external determinants of bank

profitability such as bank size, credit risk, operational efficiency, liquidity and capital strength, market structure, inflation, GDP growth among others.

The existing body of literature also covers studies on profitability of domestic and foreign banks. Williams (2007) applied the dealership model to 43 Australian banks from 1989 to 2001 and found that operating costs have a significant impact on the NIM in addition to implicit interest payments and quality of bank management. Furthermore, the sample suggested that foreign banks' NIM was significantly lower than that of the domestic banks. By estimating separate cost and profit frontiers, Berger et al. (2004) concluded that domestic banks were significantly more profitable and cost efficient than foreign banks in France, Germany and UK as opposed to Spain and US. Using a multivariate approach, K.Kosmidou et al. (2006) find that in the UK, the overall better performance of domestic banks can be attributed to a higher return on equity, ratio of net interest revenue to total earning assets, ratio of loans to customer and short-term funding as compared to the foreign banks. One of the main findings by Claessens et al. (2001) was that in developing countries foreign banks enjoyed higher interest margins and profitability as well as tax benefits (e.g. see also Demirguc-Kunt and Huizinga (1999)). Furthermore, their results suggested that the entry of foreign banks improved the domestic banking industry by inducing lower margins and a higher quality of services to the customers. In their paper, Pasiouras and Kosmidou (2007) use a balanced panel dataset of 332 domestic and 218 foreign commercial banks in 15 EU countries between 1995-2001 to examine bank profitability. Their main findings suggest that both foreign and domestic banks should efficiently control their operational cost as well as scale and scope of economies to remain profitable. External factors such as GDP and inflation had an opposite effect on domestic and foreign banks which could be attributed to the lack of country-specific macreoeconomic knowledge for foreign bank owners. More recently, Bouzgarroua et al. (2018) examines the profitability of 170 domestic and foreign banks operating in the French banking industry during 2000-2012. Their key findings suggest that foreign banks are more profitable than domestic banks due to their experience in trade finance and foreign exchange business as well as advanced customer services.

The aim of the current study is to identify which internal as well as external factors significantly impact NIM of domestic and foreign banks in EU15 over the period 2013-2017. The researcher has a priori expectations of the effect of certain variables based on the existing body of literature. As such, the goal of the paper remains to check whether those expectations are met with or the signs of the variables emerge otherwise. Based on the works of previous

authors as mentioned above, the bank-specific factors chosen are bank size, liquidity, capital strength, operational efficiency and diversification whereas the external factors are market concentration, GDP growth rate, inflation, domestic non-performing loans and domestic credit availability. The current research adds to the existing body of knowledge by using the most recent data to examine the profitability of domestic and foreign banks in 15 European countries. In terms of macroeconomic variables, GDP growth and inflation has been the most popular choice among the majority of previous studies. However, this paper will additionally include the effect of the amount of credit available to the private sector by banks and that of the proportion of non-performing loans in the country on bank NIM.

3 Variable Selection

The dependent variable used in this study is bank net interest margin (NIM) computed as a ratio of interest income net of interest expenses to average earning assets. NIM is one of the key indicators of bank profitability besides return on assets (ROA) and return on equity (ROE). It represents how efficiently the bank converts its interest bearing liabilities (deposits) to interest earning assets (loans). Banks set the funding and lending rates to safeguard their exposure to interest risk as well as to cover the cost of intermediation (Angbazo, 1997). Several authors have studied the main factors affecting NIM in the US and European banking industry Demirguc-Kunt and Huizinga (1999); Saunders and Schumacher (2000); Maudos and de Guevara (2004); Valverde and Fernandez (2007); Claeys and Vennet (2008) among others and have identified a number of internal (bank-specific) and external (industry- and country-specific) factors such as bank size, liquidity, capital strength, market structure, inflation, etc that significantly impact the bank NIM. The explanatory variables chosen in this study are described below.

In this study the effect of bank size is proxied by log of total bank assets. The existing literature on size effects is quite contradictory. Examining the profitability of Swiss banks before and during the global financial crisis in 2008-09, Dietrich and Wanzenried (2011) find that large and small commercial banks were profitable before the crisis due to the benefits of diversified activities and economies of scale. However during the crisis, large banks reported lower bank margins due to increased loan loss provisions. On the contrary, Bouzgarroua et al. (2018) report that bank size positively affects foreign banks but negatively domestic banks in the French banking industry during the financial crisis period. Both Goddard et al. (2004) and P.Athanasoglou et al. (2008) found that bank size had an insignificant effect on bank

profitability in the Greek banking market. In their study on domestic and foreign banks, Pasiouras and Kosmidou (2007) provide empirical evidence for a negative relation between bank size and profitability which supports previous findings that smaller banks enjoy economies of scale and scope as opposed to larger banks. The effect of bank size on profitability is ambiguous at this point. While the existing literature suggests that larger banks are more profitable, it may also be that the increase in size entails increased expenditure on personnel ultimately reducing profitability. Therefore the researcher has no prior expectation of bank size on NIM.

A company's financial stability is commonly measured by the ratio of equity to the total assets. Its value represents the extent to which a company's capital is funded by shareholder's equity; a higher ratio indicates lower dependence on debt financing making it relatively safer in the event of complete liquidation. The traditional risk-return view associates higher returns with higher levels of risk suggesting a negative relation between capital adequacy and bank profitability. However, on the flip side a lower leveraged bank has a high level of creditworthiness reducing its funding costs and increasing its profitability. This argument is well supported by the results of P.Athanasoglou et al. (2008), Goddard et al. (2004), Staikouras and Wood (2003). In the study conducted by Pasiouras and Kosmidou (2007) equity to assets ratio was found to be the most significant (positive) determinant of domestic bank profitability besides having a positive impact on foreign banks (e.g. see also Valverde and Fernandez (2007)). However, upon examining the Swiss banking industry, Dietrich and Wanzenried (2011) found that during the crisis period, an increase in supply of deposits coupled with a lower demand for loans and unattractive investment opportunities ultimately lowered the interest margin of banks with high capital ratios. In line with the previous literature, a positive relation between capital strength and NIM is expected.

The ratio of cost to income is one of the key measures of bank expense efficiency. Its main components includes staff salary and overhead expenses used in the everyday running of bank activities. A lower value indicates better expense management implying higher bank profitability. In their paper, Maudos and de Guevara (2004) make a notable extension of the bank dealership model of Ho and Saunders (1981) to include operating costs as a determinant of bank interest margin. They argued that banks operating at high unit costs would need to be supported by a high interest margin rendering a positive relation between the two. The variable was indeed found to be highly significant in their study and paved the way for future studies. Results obtained by Pasiouras and Kosmidou (2007) are in line with previous authors (Guru et al., 1999; Kosmidou, 2008; P.Athanasoglou et al., 2008; Dietrich and Wanzenried,

2011) suggesting a significant negative impact of cost to income ratio on bank performance especially for foreign banks operating in EU. This could be attributed to the diseconomies of scale as well as higher costs for foreign banks operating away from their home country (Berger et al., 2000). Thus, a negative impact of cost to income ratio on bank NIM is expected.

Liquidity management refers to the process of managing assets and cash flows such that the bank is able to fulfil its short-term obligations without extra funding. The current research uses the ratio of liquid assets to deposit and short-term funding obtained from Orbis BankFocus database over the period 2013-2017 to measure liquidity of the banks. A higher value of the ratio indicates that lesser funds can be loaned out by the banks which reduces the bank's interest income. Contrary to their expectation, Kosmidou (2008) found a positive but insignificant relation between liquidity and profitability of Greek banks which supported the result obtained by Bourke (1989). While Pasiouras and Kosmidou (2007) found similar results for foreign banks in EU, the domestic banks' performance in their study was negatively related to the bank liquidity (e.g. see also Guru et al. (1999); Molyneux and Thornton (1992)). In the current study, a negative impact of liquidity on bank NIM is expected.

Credit risk represents the potential loss (principal amount plus interest) faced by a bank in the case that its debtors fail to meet their obligations. It is measured by the ratio of loan loss provisions to gross loans. Loan loss reserves represent the amount of potential loan losses estimated by the bank from doubtful, written-off and charged-off loans. Loan loss provisions enter as an expense in the bank's income statement to adjust loan loss reserves as per the bank's changing views on its credit portfolio. A higher value of the ratio indicates poor asset quality and higher (perceived) credit risk. While the traditional risk-return hypothesis associates higher return with higher risk, poor asset quality may negatively impact the bank interest income. Angbazo (1997) was among the first to test the interaction between default risk, interest risk and NIM of commercial banks. The results suggested a higher sensitivity of money-center banks towards default risk while hedging against interest risk. In their study on Greek banks, P.Athanasoglou et al. (2008) find that credit risk significantly reduces bank profitability. Similarly, banks in Autralia are found to be negatively affected by credit risk in the study by Williams (2007). On the contrary, the results obtained by Maudos and de Guevara (2004) suggest that European banks transmit higher credit risk by raising their interest margins. Similarly, a positive sign is expected for the effect of credit risk on bank NIM.

The ratio of non-interest income (NII) to operating revenue represents the proportion of operating revenue that is earned mainly from fees such as deposit and transaction fees, annual

fees, inactivity fees, insufficient funds fees, penalty and over-the-limit fees from credit card holders, etc. as well as net gains on trading and derivatives, net gains on other securities and other operating income.[3] Income earned through such means enables banks to remain profitable during times of distress. Using a panel data set of US commercial banks during 1989-2001, DeYoung and Rice (2004) find that when increased marginally, NII increased bank profits while making it more volatile. However, it also worsened the average risk-return trade-off of the banks used in the sample. Valverde and Fernandez (2007) also found a significant positive impact of diversification on the interest margin of European banks. A significant negative impact of NII on bank interest margin was found by Nguyen (2012) in his study on commercial banks using a sample of 28 financially liberalized countries during 1997-2004 (e.g. see also Demirguc-Kunt and Huizinga (1999)). Furthermore, a few of the studies have associated increased reliance on non-interest income to a higher risk in banking strategies (Stiroh, 2004; Lepetit et al., 2008a; Demirguc-Kunt and Huizinga, 2010). Considering bank specialisation, the results obtained by Lee et al. (2014) suggest that while NII decreased profitability of savings banks, it had a positive impact on profitability of commercial, cooperative, and investment banks in Asia during 1995-2009. As such, it is expected that a higher share of non-interest income would lead to smaller bank NIM.

The industry-specific variable, Herfindahl index is indicative of the concentration in the banking industry (based on total assets). It is derived by summing the squares of the market shares of all the credit institutions in the banking sector.[4] Studies conducted on the impact of market structure on bank profitability are a result of two competing hypotheses: Structural-Conduct-Performance (SCP) and Efficient Structure (ES). While the former associates bank profitability with collusive behaviour among banks generating non-competitive profits, the latter argues that the bank performance is enhanced as a result of managerial and scale efficiency. A number of studies such as those of Short (1979); Bourke (1989); Molyneux and Thornton (1992); Demirguc-Kunt and Huizinga (1999) empirically support the SCP hypothesis whereas those by Smirlock (1985); Goldberg and Rai (1996); Berger et al. (2004); de Guevara et al. (2005) support the ES hypothesis. Upon examining the European banking industry as a whole in 1994-1998, the results obtained by Staikouras and Wood (2003) support neither of the two hypotheses. More recently, Pasiouras and Kosmidou (2007) found that market concentration increases foreign bank profits operating in the European market as opposed to the results of

[3] https://fred.stlouisfed.org/series/DDEI03EZA156NWDB

[4] https://sdw.ecb.europa.eu/servlet/desis?node=1000002869

Williams (2003) obtained for the Australian banking industry. A positive sign is expected for the effect of market concentration on bank NIM in support of SCP hypothesis.

Real GDP growth rate measures the economic growth of a nation from one period to the next. Since it is expressed in real terms, the growth rate is adjusted for inflation. High GDP growth reflects a booming economy characterised by expanding businesses and increased lending activity by banks which positively affects its profitability P.Athanasoglou et al. (2008). Upon estimating the effect of the business cycle on bank income statement components in 10 industrialised countries, Albertazzi and Gambacorta (2009) find that net interest income and loan loss provisions were significantly positively impacted by a change in the GDP growth rate. The study thus confirmed the pro-cyclicality of bank profitability. This argument has been further supported by the works of Goddard et al. (2004); P.Athanasoglou et al. (2008); Kosmidou (2008). Interestingly, in the study by Pasiouras and Kosmidou (2007), profitability of domestic banks was positively impacted by GDP growth rate as opposed to that of foreign banks examined in 15 European countries over the period 1995-2001. Furthermore, the results obtained by Staikouras and Wood (2003) suggest a negative relation between GDP and profitability of the European banking industry over the period 1994-98 which could be due to the increased amount of credit supply in the economy. As such, it is expected that GDP will have a negative effect on bank NIM.

The existing literature also suggests a significant relation between inflation and bank profitability. It is measured by the consumer price index which reflects the year-on-year change in the value of a basket of goods. Revell (1979) was among the first to document the relation between inflation and bank profitability based on how operating costs would be affected by inflation. Perry (1992) argued that bank profitability depended on whether inflation was fully anticipated by the bank management. Timely anticipation of inflation would enable the banks to adjust their lending rates such that revenue increases faster than costs leading to higher profitability. On the demand side, inflation may disrupt the regular cash flows of customers reducing their demand for financial services. In their study P.Athanasoglou et al. (2008) find the partial anticipation of inflation by the bank management as well as information asymmetry (between the bank management and customers) to enhance bank profitability. Similarly, Bourke (1989); Molyneux and Thornton (1992); Demirguc-Kunt and Huizinga (1999); Claessens et al. (2001); Demirguc-Kunt et al. (2003); Claeys and Vennet (2008) have reported a significant positive impact of inflation on bank NIM. On the other hand, the key findings by Boyd et al. (2001) empirically support a significantly negative and economically important non-linear effect

of inflation on financial sector performance. Comparing domestic and foreign banks in fifteen European countries, Pasiouras and Kosmidou (2007) find that while domestic banks profit from timely expectation of inflation and adjustment of lending rates, foreign banks suffer due to lack of knowledge of the macroeconomic environment in the host country. Since the effect of inflation is subject to timely anticipation by the banks, there is no a priori expectation of its sign.

Another variable of interest is the domestic credit provided to the private sector by banks (as a percentage of GDP). It includes lending of financial resources through loans, purchases of non-equity securities, and trade credits and other accounts receivable by depository corporations (excluding central banks) to the private sector.[5] The private sector of any economy is instrumental in stimulating its growth and productivity by creating more jobs and income sources. Based on the rules of demand and supply, it is expected that higher the amount of credit available, lower will be the lending rates offered by banks. Ceteris paribus this implies a negative impact of domestic credit available on bank NIM.

In addition, the current study also considers the effect of the ratio of bank non-performing loans (NPL) to gross loans on bank profitability for each of the fifteen European countries. It is computed by dividing the gross value of the loans as recorded on the balance sheet by the total value of the loan portfolio (including nonperforming loans before the deduction of loan loss provisions).[6] The ratio measures the asset quality which impacts the overall health and stability of the financial sector. In order to the cover the credit risk faced by the economy, it is expected that the banks will charge a higher interest on loans, thus positively impacting the bank NIM.

4 Data

The sample for the current study consists of 426 banks from 15 European countries over the period 2013-17. A balanced panel dataset is obtained by filtering through active banks with the mentioned specialisation: commercial, cooperative, savings, and real estate and mortgage banks. Furthermore, the ownership structure was determined based on 50.1% ownership of the shares of the bank, dividing the sample into domestically and foreign owned banks. The data was further cleaned by removing fields containing missing values for either the dependent or explanatory variables. The number of banks in each sub-group is mentioned in the table below.

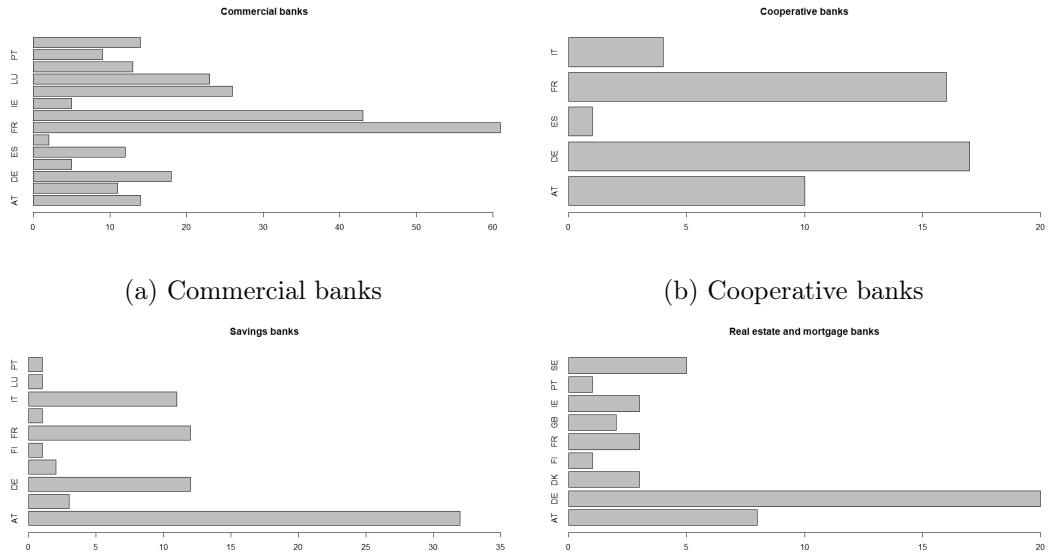
[5] https://data.worldbank.org/indicator/FD.AST.PRVT.GD.ZS

[6] https://data.worldbank.org/indicator/FB.AST.NPER.ZS?view=chart

	Domestic	Foreign
Commercial	137	119
Cooperative	48	0
Savings	72	4
Real Estate & Mortgage	40	6
Total	297	129

Table 1: Sub-division of sample based on specialisation and ownership

Figure 1 presents the number of banks located in each of the 15 EU countries chosen for this study. A quarter of the commercial banks are located in France followed by 18% located in United Kingdom. Germany and France contribute equally to the sample of cooperative banks, whereas, Austria contains the maximum number of savings banks in the sample. Lastly, with respect to real estate and mortgage banks, Germany contains almost 45% of the total sample.



(a) Commercial banks

(b) Cooperative banks

(c) Savings banks

(d) Real estate & Mortgage banks

Figure 1: Number of banks in located in each country

The dependent variable is net interest margin (NIM) for which annual observations are obtained at the bank-level for the sample period 2013-2017 from the Orbis BankFocus database.[7] The bank-specific variables mentioned in section 3 are proxied by annual financial ratios obtained from BankFocus database for the same period. The effect of bank credit risk is measured by calculating the ratio of loan loss provisions to gross loans in millions of euros, both of which are observed at the bank-level from the database. An overview of the variables and their expected

[7] BankFocus database succeeds the BankScope database maintained by Bureau van Dijk which is unavailable after December, 2016.

signs can be found in the table below.

Table 2: Bank-specific characteristics with expected signs

Variable	Measure	Expected Sign
Bank size	Log(total assets)	?
Capital adequacy	Equity/total assets	+
Operating efficiency	Cost/income	-
Liquidity	Liquid assets/deposits& short-term funding	-
Bank credit risk	Loan loss provisions/gross loans	+
Diversification	Non-interest income/operating revenue	-

Note: Annual data for the above mentioned variables is obtained for the sample period 2013-17.

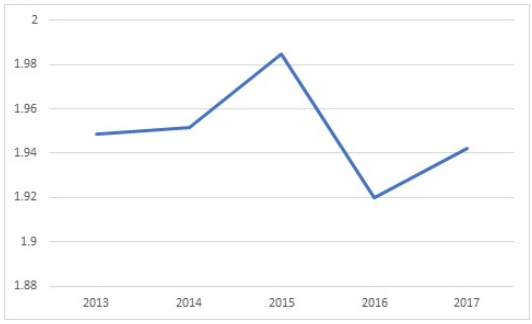
Table 3 mentions the various industry- and country-specific variables chosen in the current research as well as expected signs. Concentration in the banking sector is measured by the Herfindahl-Hirschman index obtained from the website of Statistical Data Warehouse for the period 2013-2017. Country-specific variables which include real GDP growth rate, inflation as measured by the consumer price index, domestic credit availability and credit risk of nation are obtained from the website of World Bank for each of the 15 countries over the period 2013-17. In the current study, annual observations of both industry- and country- specific variables are used.

Table 3: Industry- and bank-specific characteristics with expected signs

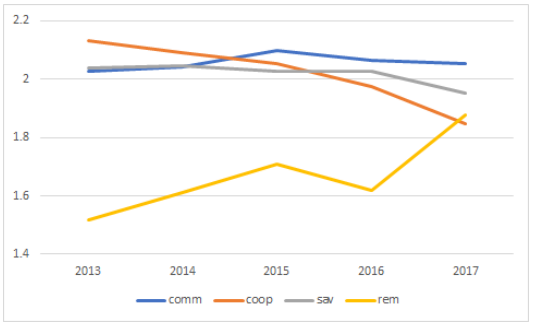
Variable	Measure	Expected Sign
Market concentration	Herfindahl Index	+
Economic growth	Real GDP growth rate	-
Inflation	Change in consumer price index	?
Credit risk of economy	Non-performing loans/gross loans	+
Domestic credit availability	Domestic credit provided to the private sector by banks/GDP	-

Note: Annual data for the above mentioned variables is obtained for the sample period 2013-17.

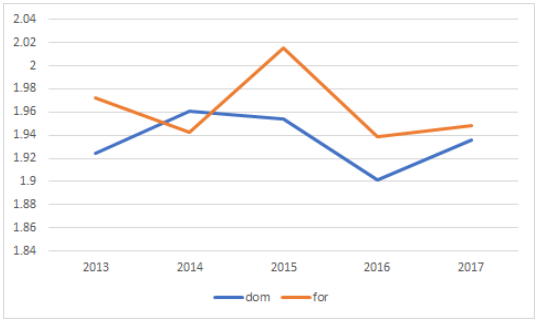
The graphs presented in figure 2 show how the average NIM of the total banks behaves over the span of the sample period for different specialisations as well as ownership structures. In figure 2a, NIM does not show any trend as the it seems to hover around its mean value of 1.95. Figure 2b represents how the NIM of different specialised banks evolves over time. The interest margin of real estate and mortgage banks is consistently lower than the other categories with an upward trend. In contrast, the average NIM's of cooperative and savings banks show a downward pattern over time.



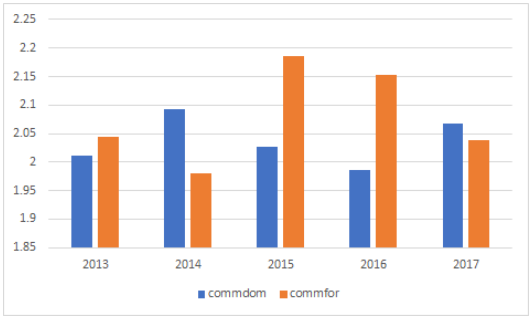
(a) Evolution of average NIM



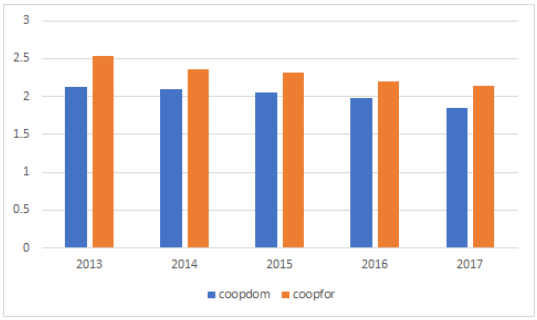
(b) Average NIM as per specialisation



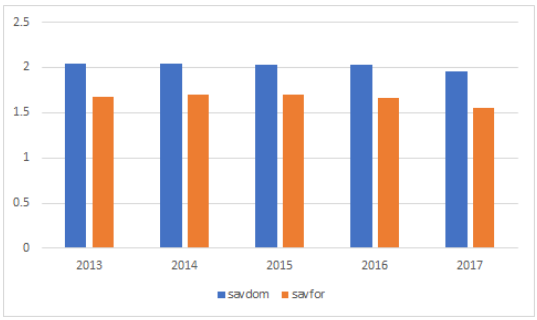
(c) Average NIM as per ownership



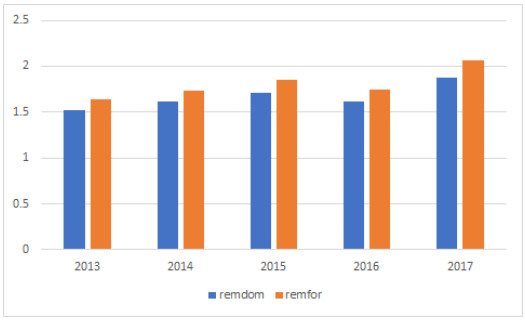
(d) Average NIM of domestic vs. foreign commercial banks



(e) Average NIM of domestic vs. foreign cooperative banks



(f) Average NIM of domestic vs. foreign savings banks



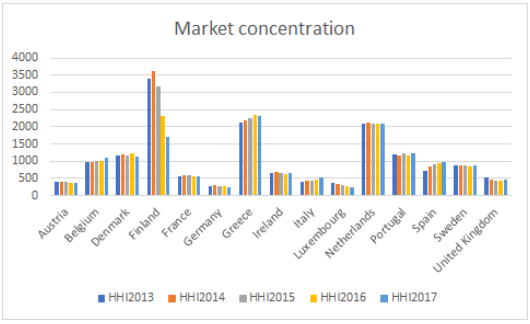
(g) Average NIM of domestic vs. foreign REM banks

Figure 2: Average NIM as per ownership and specialisation

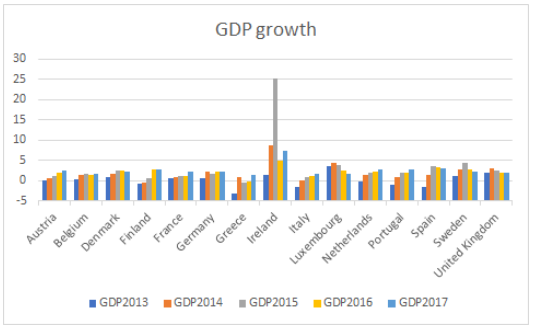
Based on ownership structure, it can be observed from figure 2c that on average foreign banks record a higher NIM than domestic banks over the sample period. Earning a higher

NIM may act as a safety net for foreign banks against the macroeconomic risk of operating in a host country.

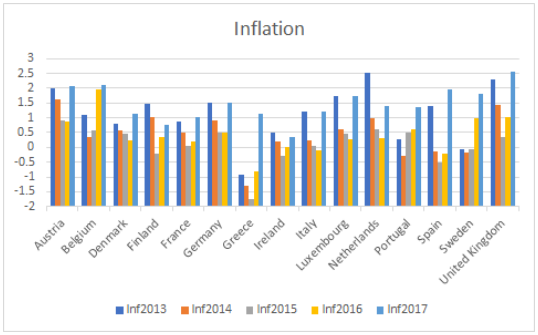
Upon comparing domestic and foreign banks across specialisation, it is observed that the interest margin of foreign cooperative and real estate and mortgage banks is consistently higher than that of the domestic banks. The opposite is observed for savings banks wherein domestic banks operate at a higher NIM across the sample period.



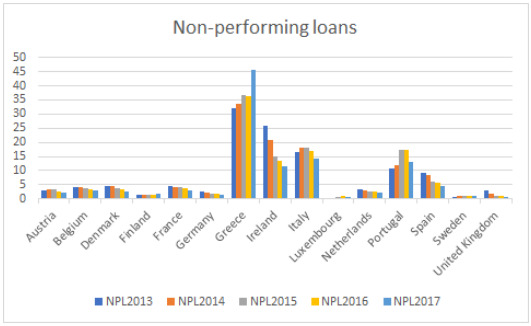
(a) Evolution of Market concentration



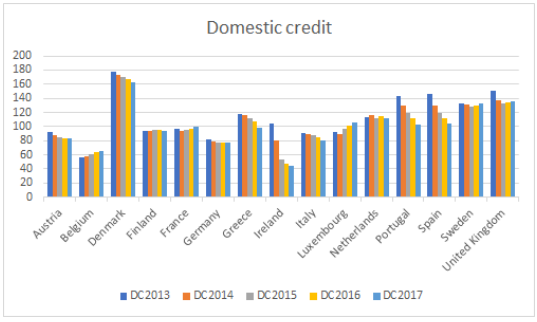
(b) Evolution of GDP growth



(c) Evolution of Inflation



(d) Evolution of Non-performing loans



(e) Evolution of Domestic credit

Figure 3: Evolution of industry- and country-specific variables

Figure 3 graphically represents the behaviour of the chosen industry- and country-specific variables for each of the 15 EU countries included in the sample. Figure 3a presents the levels of market concentration in the different countries. The Finnish banking sector is observed to be the most concentrated since it is dominated by four large groups which account for 81% of

the total market share and are under the direct supervision of the European Central Bank.[8] On the other hand, the German banking market is the least concentrated among the other countries in the sample which can be attributed to the highly competitive and low profitability of German banks. In figure 3b it is interesting to see that Ireland sees a sharp rise in the GDP growth rate in 2015 with an average growth rate of 25.11% which is almost thrice of what was expected. The Irish economy thrives on foreign trade and investment as well as industrial production. The low corporate tax rates were instrumental in attracting global and multinational companies to set up their bases in Ireland and contribute to their GDP through increased sales.[9] In figure 3c Greece is observed to have the lowest rate of inflation which can be attributed to the Greek financial debt crisis characterised by a severe economic downturn, rising debt and unemployment and negative inflation. In figure 3d, while non-performing loans make up 37% of the gross loans of Greek banks, Luxembourg and Sweden are among the countries with the lowest value of non-performing loans to gross loans which reflects their economic strength. Denmark is observed to have the highest level of domestic credit in figure 3e which can be attributed to a well-developed financial system coupled with a high demand of debt from households to purchase homes and cars. [10]

[8] https://www.ebf.eu/finland/

[9] http://www.oecd.org/sdd/na/Irish-GDP-up-in-2015-OECD.pdf

[10] http://www.nationalbanken.dk/en/publications/themes/Pages/Household-wealth-and-debt.aspx

Descriptive Statistics

Table 4: Descriptive statistics of bank-, industry- and country-specific variables

	Mean	Std. dev.	Min.	Max.
NIM	1.95	1.51	-0.78	13.83
Bank size	8.16	2.20	2.68	14.37
Capital strength	9.87	8.44	0.11	90.70
Operational Efficiency	69.22	29.85	1.95	401.01
Bank credit risk	0.60	2.03	-27.28	30.11
Liquidity	30.84	37.18	0.06	569.55
Diversification	35.88	27.53	-197.22	133.26
Market concentration	1,028.84	782.86	2500	3,630
GDP	2.05	3.23	-3.24	25.12
Inflation	0.71	0.86	-1.74	2.56
Non-performing loans	7.69	9.83	0.21	45.57
Domestic credit	104.77	29.51	44.69	177.01

Note: The descriptive statistics for the bank-specific variables are calculated across the cross-sectional units and over time. The statistics for industry- and country-specific variables are calculated across the 15 European countries and over time.

Table 4 presents the descriptive statistics of the dependent and explanatory variables which are computed across the cross-sectional units as well as over time. The dependent variable is bank NIM which has an average value of 1.95% which is indicative of the low profitability environment banks are operating in, post the financial crisis. It also suggests a competitive European banking industry which keeps the bank margins low. The mean value of operational efficiency is at 69% which represents higher costs as a percentage of income of the banks reflecting cost inefficiency in the European banking industry. Market concentration has a very high standard deviation which reflects how widely spread the data is around its mean value of 1028.84. The overall inflation level over the sample period is well below the target rate of 2% set by the European Central Bank. While the highest value of inflation pertains to UK, negative inflation rates were recorded for Greece as a result of its poor economic conditions which lead to its bankruptcy. With a standard deviation of 0.86, it is evident that the inflation levels in the 15 European countries do not vary much suggesting overall price stability in the European market. An average value of 104.77% indicates that the domestic credit available is more than proportional to the total value of the GDP which positively influences the overall economic growth and productivity.

Table 10 in Appendix presents the correlation coefficient among the variables in the current

study. The values above the diagonal reflect the Pearson correlation also known as 'product moment correlation coefficient'. It takes a value between -1 and +1 indicating the strength of linear correlation between two variables. The values in bold are significant at 5% level of significance. In the current sample of banks, capital strength and bank credit risk are the only variables which are significantly positively correlated with the dependent variable. The remaining bank-specific as well as industry- and country-specific variables are negatively correlated with bank NIM. Among the explanatory variables, it is observed that bank size and capital strength have a significant negative correlation which indicates that larger the bank, the more dependent it is on external sources of funding. Capital strength has a strong positive correlation with liquidity implying that more liquid assets the bank holds, the lesser leveraged it is. As such banks are able to fund themselves using internal sources and thus depend lesser on external debt funding. GDP and NPL are strongly negatively correlated which makes economic sense. An increase in GDP growth rate is indicative of a booming economy accompanied by an overall growth in productivity during which the chances of credit default are expected to be low.

5 Methodology

Panel data models capture variation across two dimensions: cross-sectional and over time. They are estimated under two main settings namely static and dynamic. A general linear specification of panel data is as follows:

$$y_{it} = \mu_{it} + \beta_{it} x_{it} + \varepsilon_{it}$$

where, $i = 1, ..., N$ represents the number of cross-sectional units and $t = 1, .., T$ represents the number of time periods. μ_{it} represents the constant associated with every individual i at time period t and β_{it} is the coefficient of the explanatory variable x_{it}. ε_{it} is the unobserved error term for individual i at time period t. Estimation of different parameters for each i and t maybe difficult, as a result of which certain restrictions need to be imposed on μ_{it} and β_{it} as well as the unobserved error term ε_{it}.

Pooled ordinary least squares (OLS), fixed effects and random effects models are the most popular methods to estimate static panel data. However, their restrictive nature is not offset by the computational ease and parsimony offered by them. Pooled OLS restricts heterogeneity

in both dimensions (N and T) by assuming μ and β to be constant for all individuals i over all the time periods t. Individual-specific effect models capture individual heterogeneity by allowing μ to vary across the N units.

$$y_{it} = \mu_i + \beta x_{it} + \varepsilon_{it}$$

where, μ_i represents the individual-specific fixed effects. The fixed effects model assumes correlation between μ_i and x_{it} which renders the pooled OLS estimates inconsistent due to the inherent endogeneity. The 'within' and 'first difference' estimators are consistent and exploit the time-variation in every $i = 1, ..., N$ whilst eliminating time-invariant characteristics of the individual units. [11]. On the other hand, random effects model assumes individual-specific effects to be independent of the explanatory variables and part of the unobserved error term ε_{it}. As the name suggests, the 'between' estimator measures variation between the N cross-sectional units by taking a time-average of individual observations, thus ignoring time-variation in the observations. It produces consistent but inefficient estimates of pooled and random effects models. By incorporating the correlation in the error terms, (feasible) generalised least squares (GLS) increases efficiency of the estimator.

Dynamic panel models include the lagged dependent variable $y_{i,t-1}$ as a regressor.

$$y_{it} = \delta y_{i,t-1} + x'_{it}\beta_{it} + \varepsilon_{it} \tag{1}$$

$$\varepsilon_{it} = \mu_i + u_{it}$$

The non-zero correlation between and $y_{i,t-1}$ and μ_i in the error term which causes endogeneity, which renders the estimates produced by pooled OLS and individual-specific effect models, biased and inconsistent. This bias is commonly referred to as the 'dynamic panel bias' or 'Nickel bias' Roodman (2009a). In order to get rid of the fixed effects, data can be transformed by taking the first difference of (1). The equation can then be estimated by using instrumental variables within the generalised method of moments (GMM) framework.

The general idea of GMM revolves around estimating parameters by solving sample *moment* conditions that mimic those of the population. The downside to this method is the potential endogeneity between the first differenced $y_{i,t-1}$ and the first differenced error term ε_{it} inspite of

[11] The 'within' estimator eliminates the fixed effects by estimating the difference between each observation y_{it} and its time average $\overline{y_i}$, whereas the 'first difference' estimator eliminates the fixed effects by estimating the difference between y_{it} and its immediate lagged value $y_{i,t-1}$

eliminating the fixed effects μ_i. This justifies instrumenting the lagged dependent variable. A good instrument is one which is highly correlated with the explanatory variable but not with the unobserved error term. The earliest IV estimator was developed by Anderson and Hsiao (1982) which used the immediate lag of y_{it} in levels and difference to solve the moment conditions. Although consistent, this estimator is inefficient as it only uses information from $t-1$ lag. Efficiency of the estimator can be further improved by incoroporating more information from longer lags of the variables. The difference GMM estimator developed by Arellano and Bond (1991) instruments the differenced lagged dependent variable by using longer lags of the y_{it} in levels. Taking a step further, Blundell and Bond (1998) developed the system-GMM estimator which is obtained by using differenced instruments for the potentially endogenous variables in levels. As such, system-GMM estimates the parameters using two sets of equations; first, the first-differenced equation for each y_{it}, where instruments for the endogenous variables are in levels, and second, equation in levels for each y_{it} which uses first-differenced instruments for the endogenous variables. Additionally, system-GMM offers the advantage of including time-invariant variables which would be eliminated in difference GMM.

In line with the empirical estimation technique used by Athanasoglou et al. (2008), Herrero et al. (2009) and Dietrich and Wanzenried (2011) the following linear model specification describes the effect of various internal and external factors on bank NIM:

$$\Pi_{it} = \delta\Pi_{i,t-1} + \sum_{b=1}^{4} \alpha_b X_{b,it} + \sum_{m=1}^{3} \beta_m Y_{m,t} + \varepsilon_{it}, \tag{2}$$

$$\varepsilon_{it} = \mu_i + u_{it}$$

where Π_{it} is the NIM of bank i at time t, $i = 1, .., 426$ and $t = 2013, .., 2017$. For every bank i at time t, the bank-specific characteristics are contained in the vector $X_{b,it}$ with the associated vector of coefficients α_b. Similarly, $Y_{m,t}$ represents the vector of industry- and country-specific variables at time t and β_m is the vector of their coefficients. ε_{it} consists of μ_i and u_{it} which represent the unobserved individual effects and the idiosyncratic error term for each bank i at time t. Equation 2 is a one-way error component regression model, where $\mu_i \sim \text{IIN}(0,\sigma_\mu^2)$ and is independent of $u_{it} \sim \text{IIN}(0,\sigma_u^2)$.

Based on the correlation structure between the explanatory variables, four bank-specific, and two country-specific variables are chosen in addition to the industry-specific variable to prevent multicollinearity in the model 2. Thus a total of seven explanatory variables are used

to estimate bank NIM namely, bank size, bank credit risk, diversification, operational efficiency, market concentration, inflation and non-performing loans. The variable, 'non-performing loans' is first-differenced to eliminate the downward trend it exhibits.

Berger et al. (2004) identify a number of factors that explain the persistence of profits in the banking industry, namely an imperfectly competitive banking market, information asymmetry as well as sensitivity to country-specific macroeconomic shocks. Thus, bank profit at time t tend to be correlated with its lagged values. To account for such serial correlation, the linear model 2 is dynamically specified by incorporating the lagged NIM term $\Pi_{i,t-1}$. In the equation, δi represents how quickly the NIM of bank i adjusts to its equilibrium level over time. A positive value of δ between 0 and 1 implies that bank profits are persistent and eventually return to their average value. A value close to 0 indicates a roughly competitive market due to low persistence in bank profits, whereas, a value close to 1 indicates a low degree of competition in the banking market.

In their paper, Herrero et al. (2009) describe a number of challenges in estimating bank profitability. One such challenge is the problem of endogeneity; banks that are already more profitable can reinvest the profits to increase their equity. They could also increase their expenditure on advertising to further grow in size ultimately affecting bank profitability. This rationale could also have an opposite impact: hiring more personnel can reduce operational efficiency which may reduce profits too. Furthermore exists the problem of heterogeneity among the banks which arises due to various factors such as size, business model, differences in corporate governance which are usually difficult to capture. In light of the above mentioned problems, this study employs system generalised method of moments (GMM) developed by Blundell and Bond (1998). System-GMM supports a dynamic setting to explain the dependent variable by incorporating its lagged value in levels and differences as instruments along with lagged values of other potentially endogenous regressors. The system-GMM estimator is thus consistent as it controls for endogeneity, any unobserved heterogeneity and persistence of profit.

Although system-GMM still remains a popular choice among researchers for dynamic panel data estimation, Roodman (2009b) brought to light the problem of instrument proliferation. This refers to the problem of too many instruments for the endogenous explanatory variables. Overfitting introduces a bias in the estimates which is not offset by the gain in efficiency due to increased moment conditions. He mentions two ways of reducing the number of instruments: the first, to limit the number of instruments by selecting certain lags out of all the available ones, in each time period t (such that it is linear in T). The second method entails creating

smaller groups of instruments by combining them through addition. These groups potentially carry more information since all the lags of the endogenous explanatory variables are utilised.

Equation 2 is estimated using the function *pgmm* from the *plm* package in the statistical software R. The dependent variable is regressed on its immediate lagged value in addition to current and immediate lagged values of the explanatory variables. Due to the potential endogeneity caused by lagged NIM, second upto the fourth lagged values of the dependent variable are used as GMM instruments. The remaining explanatory variables are assumed to be exogeneous in the current study. [12] The model as described in the 5 section consists of a one-way error component. Thus, it is estimated using the 'individual' effects setting. Additionally, 'twostep' covariance matrix is used which produces consistent and aymptotically efficient estimates. Lastly, the problem of too many instruments is tackled by using the 'collapse' option in the *pgmm* function.

A number of diagnostic tests will be performed to gauge the robustness of the system-GMM estimators. The Sargan test will test whether the moment conditions imposed by the instrument variables over-identify the model. Secondly, the Arellano-Bond AR(1) and Arellano-Bond AR(2) tests will test for the presence of and absence of serial correlation in the error terms respectively. First order serial correlation in the error term is expected due to the inclusion of the lagged dependent variable in equation 2. Lastly, Wald test is performed to test the overall significance of the model.

6 Univariate Analysis

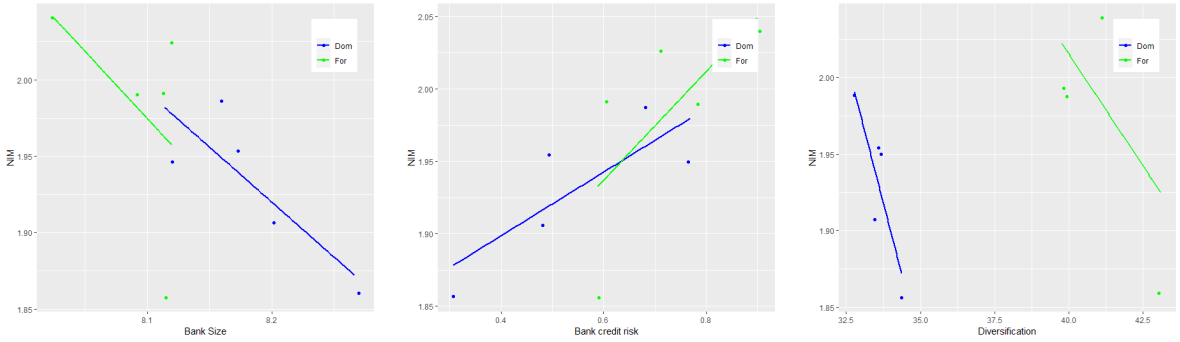
This section graphically represents how the dependent variable for the sub-samples of domestic and foreign banks is impacted by each one of the explanatory variables in isolation. The aim of the univariate analysis is also to check whether the effect of the explanatory variables on the NIM of both domestic and foreign banks is consistent as well as to have some prior expectation of the signs based on the current sample. The dependent variable NIM and the bank-specific variables are averaged over the cross-sectional (bank) units, whereas the industry- and country-specific variables were averaged over the sample of the 15 European countries, for each year of the sample time period 2013-17, thus yielding 5 data points. The plots were obtained by regressing NIM on each of the seven explanatory variables [13] included in the model

[12] The equation in levels is instrumented by second upto the fifth lagged values of the differenced variable NIM_{t-1}, whereas, the equation in differences is instrumented by the variable in levels.

[13] Bank size, bank credit risk, operational efficiency, diversification, market concentration, inflation and non-performing loans

using a linear model for the sub-samples of domestic and foreign banks.

The first graph in figure 4 presents the effect of bank size on bank NIM which is captured by regressing NIM on the natural log of total bank assets. A strong negative slope is observed for both the groups of banks which suggests that larger banks irrespective of their ownership structure, fail to enjoy economies of scale which has a negative impact on their NIM. The second graph shows a positive slope obtained by regressing NIM on the ratio of bank-level loan loss provisions to gross loans for both the sub-samples. This makes economic sense since banks charge a higher interest on their loans to cover the credit default risk perceived by them. The ratio of non-interest income to operating revenue of the bank represents how diversified the bank is in terms of non-interest activities. In the third graph, diversification is observed to negatively affect NIM of both the sub-samples suggesting that the more diversified the bank is, the lesser it has to rely on the net interest margin it earns from loans and deposits. The fourth graph presents the negative effect of operational efficiency on the NIM of both domestic and foreign banks, which is in line with the researcher's expectation that higher cost to income ratios suggest inefficient management which prevents banks from earning a high interest margin. Market concentration as measured by the Herfindahl index (HHI) is indicative of the degree of competition that exists in the banking market. The fifth graph in figure 4 suggests an average positive impact of market concentration on the NIM of both domestic and foreign banks. This makes economic sense since a highly concentrated banking market enables the major players to earn non-competitive profits.



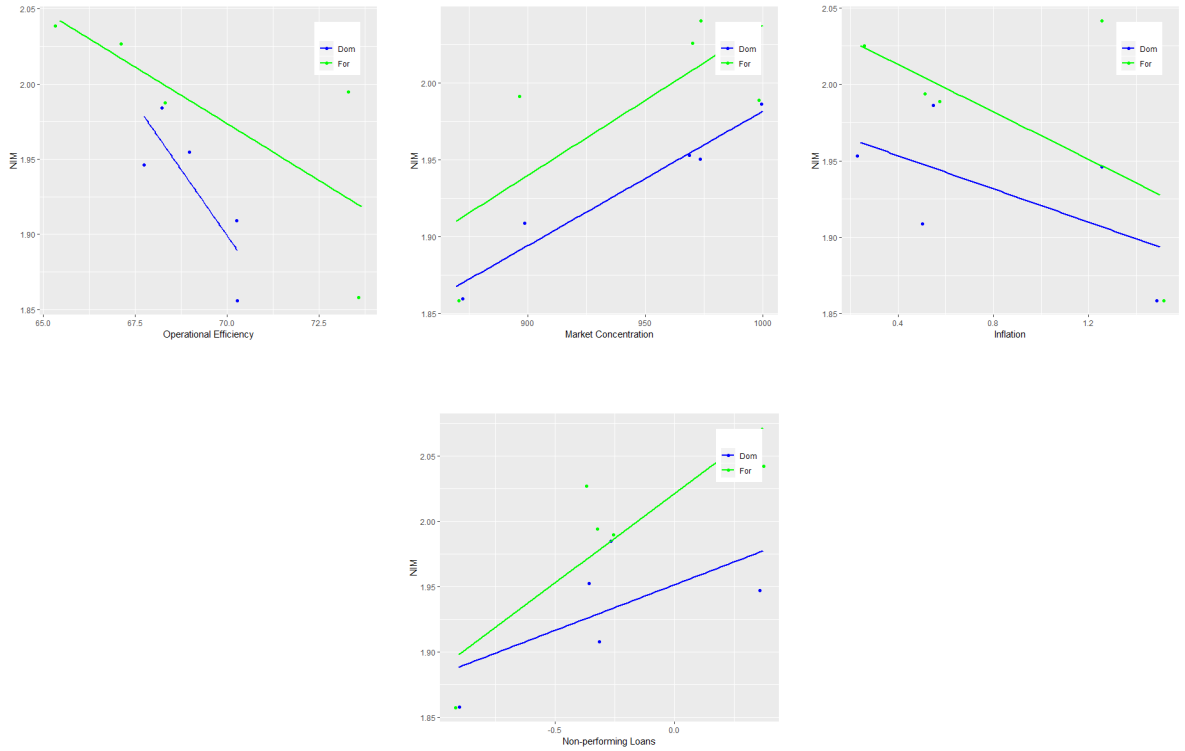


Figure 4: Univariate regression of NIM on each of the explanatory variables

The effect of inflation depends upon whether the banks anticipate the inflation in time to adjust their interest rates. The downward sloping regression line in the sixth graph suggests that on average, an increase in the rate of inflation decreases the net interest margin earned by the current sample of domestic and foreign banks. Lastly, The ratio of non-performing loans to gross loans represents the credit risk present in the economy. The upward sloping line suggests that higher the ratio of non-performing loans, higher the net interest margin which acts as a buffer for banks facing the credit risk.

It must be noted that the results obtained from the univariate regression of the dependent variable NIM on the explanatory variables ignores the panel structure of the data and treats the average values obtained for the five years as independent data points as opposed to system-GMM which is the main methodology employed by the current study.

7 Results

Table 5 presents the results obtained by performing system-GMM on the entire sample of 426 banks followed by the sub-samples of domestic and foreign banks. For all the three cases, lagged NIM is used as an explanatory variable under the dynamic panel data setting in addition to

the bank-, industry- and country-specific variables.

A p-value of 0.283 is obtained for the Sargan test which does not reject the null hypothesis of valid instrument variables (uncorrelated with the error term), at all conventional levels of significance. The presence of first order autocorrelation in the error terms is supported by a p-value of 0.0004, whereas a p-value of 0.341 supports the absence of second order autocorrelation in the error terms. The Wald test statistic attains a value of 39310.49 with a p-value almost equal to zero, thus making the overall model significant at 10%, 5% and 1% levels of significance. Similar test statistics are obtained for the sub-samples of domestic and foreign banks.

The AR(1) term associated with the lagged dependent variable takes a highly significant value of around 0.87 for all three samples which justifies the use of system-GMM. Such high persistence of profits suggests how concentrated the European banking market is enabling banks to earn non-competitive profits. Based on the literature, there was no a priori expectation of the effect of bank size on its net interest margin. In the current study, bank size has a significant negative impact on net interest margin across all the three samples. This result is in accordance with that found by Pasiouras and Kosmidou (2007) who conclude that economies of scale are enjoyed by smaller banks rather than the larger banks. Furthermore, larger banks operating in foreign countries do not benefit from local economies of scale resulting in increased operating expenses and overheads which may not be covered by the NIM earned by the bank.

The next bank-specific variable of interest is bank credit risk. Measured by the ratio of bank-level loan loss provisions to gross loans, it is found to have a significant positive impact on the net interest margin of the entire sample of banks as well as the foreign banks. The effect on domestic banks is positive albeit insignificant. This is consistent with the prior expectation of the researcher as well as the result obtained by Maudos and de Guevara (2004) suggesting that in order to cover their potential losses from doubtful and written-off loans, banks would increase the interest charged on its credit portfolio and lower the interest paid on the deposits, thereby widening the NIM earned by them.

In line with what was expected, a significant negative impact of operational efficiency on bank NIM is observed for the entire sample and foreign banks. A high cost to income ratio implies lesser efficient management of expenses as well as bank management which affects bank performance and ultimately bank profit. A competitive banking environment in the host country further prevents foreign banks from passing on the increased costs to their customers thereby eating into the bank's profit. This negatively affects the net interest margin earned by the banks.

Table 5: Estimated system-GMM coefficients for the entire bank sample, domestic and foreign banks

	Dependent variable: NIM		
	All banks	Domestic banks	Foreign banks
NIM_{t-1}	0.891^{***}	0.873^{***}	0.861^{***}
	(0.041)	(0.055)	(0.083)
Bank size	-0.469^{***}	-0.625^{*}	-0.512^{**}
	(0.165)	(0.360)	(0.255)
Bank credit risk	0.051^{***}	0.028	0.060^{**}
	(0.017)	(0.024)	(0.029)
Operational efficiency	-0.003^{**}	-0.002	-0.004^{*}
	(0.001)	(0.002)	(0.002)
Diversification	-0.014^{***}	-0.011^{***}	-0.014^{***}
	(0.004)	(0.003)	(0.005)
Market concentration	0.00004	0.0001	-0.0004
	(0.0001)	(0.0001)	(0.001)
Inflation	-0.005	-0.009	-0.028
	(0.013)	(0.020)	(0.026)
Non-performing loans	-0.020^{**}	-0.016	-0.020
	(0.010)	(0.013)	(0.020)
Observations	426	297	129
Sargan test	0.283	0.305	0.305
AB test AR(1)	0.0004	0.0098	0.0233
AB test AR(2)	0.341	0.453	0.322
Wald test $\chi^2(15)$	39310.49	26270.65	16264.54

Note: The above table reports the coefficients estimated by applying system-GMM on the entire sample of 426 banks, 297 domestic and 129 foreign banks. The dependent variable is net interest margin of the banks. The explanatory variables include lagged dependent variable in addition to bank-, industry- and country-specific variables. The sample period ranges from 2013-17. Coefficients marked with ***, ** and * indicate that their p-value is lesser than 0.01, 0.05 and 0.10 respectively. The standard errors in the parenthesis are auto-correlation and heteroskedasticity robust. Critical value of $\chi^2(15)$ is 24.996 at 5% significance level.

A significant negative relation is found between diversification measured by the ratio of non-interest income to operative revenue across the three samples. This in line with the findings of previous studies which suggest that the benefit of an increased proportion of operating

revenue coming from service fees and commission income can be transmitted to the customers by either lowering the interest charged on loans, increasing the interest paid on deposits or both.

In the current study, market concentration is found to be insignificant in explaining the variation in bank NIM. Nevertheless, it positively impacts the NIM of the entire sample as well as the sub-sample of domestic banks as opposed to negatively impacting foreign banks' NIM. Thus, a weak evidence is provided for the SCP hypothesis which proposes that a highly concentrated market encourages collusive behaviour among the big market players which allows them to generate non-competitive profits. However, it is possible that since the host banking market is dominated by a few domestic players, it may me difficult for foreign banks operating at competitive prices to earn a higher margin.

Inflation is observed to have an insignificant negative impact on the overall sample as well as on both the sub-samples. The result obtained can be attributed to untimely anticipation of inflationary pressure by the banks irrespective of their ownership structure. It prevents the banks from adjustment of interest rates and effective cash flow management to counter the effect of inflation in the future, directly impacting personnel and operating expenses ultimately affecting bank profitability. On the demand side, consumers may also experience disturbed cash flows which reduces their demand for credit alongside their ability to repay the borrowed loans.

The final country-specific variable is the ratio of non-performing loans to gross loans in the economy which represents the domestic credit risk. It has a negative effect on the NIM of the banks irrespective of their ownership structure which is in line with the prior expectation of the researcher. A higher amount of NPL in the economy eats into the profits of the banking industry due to the amount of lost principal as well as the interest on the credit portfolio.

As a robustness check, the effect of the explanatory variables on bank NIM was also estimated using pooled OLS, fixed and random effects model for the entire sample. Table 6 presents the results of the same. The potential endogeneity introduced in the model due to the lagged NIM renders the parameter estimates biased and inconsistent. For all three methods, the computed standard errors are cluster robust which allows the standard errors within a cluster to be robust to heteroskedasticity and serial correlation.[14] The results obtained are consistent with those obtained by system-GMM in terms of the signs of the coefficients obtained.

[14] The current sample contains banks from 15 European countries as well as banks across four specialisations and it may be that the unobservable fixed effects are correlated within the cluster. Thus, using cluster robust standard errors makes them robust to hetereskedasticity and serial correlation within each cluster.

Table 6: Result of pooled OLS, fixed and random effects on the entire sample of banks

	Dependent variable: NIM		
	Pooled OLS	Fixed effects	Random effects
NIM_{t-1}	0.919***	0.225***	0.895***
	(0.029)	(0.029)	(0.029)
Bank size	−0.013*	−0.421***	−0.019***
	(0.007)	(0.007)	(0.007)
Bank credit risk	0.033**	0.029**	0.036***
	(0.014)	(0.014)	(0.014)
Operational efficiency	0.0003	−0.003***	0.0001
	(0.001)	(0.001)	(0.001)
Diversification	−0.003***	−0.013***	−0.003***
	(0.001)	(0.001)	(0.001)
Market concentration	0.00000	−0.00000	−0.00000
	(0.00004)	(0.00004)	(0.00004)
Inflation	−0.017	−0.050**	−0.029
	(0.021)	(0.021)	(0.021)
Non-performing loans	−0.007	0.013	−0.006
	(0.012)	(0.012)	(0.012)
Constant	0.307*		0.457***
	(0.165)		(0.165)
Observations	426	426	426
R squared	0.889	0.209	0.851
Wald test $\chi^2(8)$	13700	336.17	9725.6

Note: The above table reports the coefficients estimated by applying pooled OLS, fixed effects and random effects on the entire sample of 426 banks The dependent variable is net interest margin of the banks. The explanatory variables include lagged dependent variable in addition to bank-, industry- and country-specific variables. The sample period ranges from 2013-17. Coefficients marked with ***, ** and * indicate that their p-value is lesser than 0.01, 0.05 and 0.10 respectively. The standard errors in the parenthesis are cluster robst. Critical value of $\chi^2(8)$ is 15.507 at 5% significance level.

As expected, the coefficient of the lagged dependent variable obtained from pooled OLS is biased upwards whereas that obtained from within estimator is biased downwards (Roodman,

2009b) such that the lagged parameter estimated by system-GMM lies between the two values.

Additionally, tables 8 and 9 in the Appendix present the results of a 'kitchen-sink' regression, i.e. estimating the effect of all the eleven regressors chosen by the researcher. The regression is done usign both system-GMM as well as pooled OLS, fixed and random effects.

8 Monte Carlo Simulation

With the help of Monte Carlo simulation, the performance of system-GMM is evaluated for different values of N and T which represent the number of cross-sectional units and time periods respectively. The simulation is designed in the spirit of Soto (2009) which replicates the model used by Blundell et al. (2000). For the purpose of simulation the following autoregressive model with one explanatory variable is considered.

$$y_{it} = \alpha y_{i,t-1} + \beta x_{it} + \eta_i + u_{it}$$

for $i = 1, .., N$ and $t = 2, .., T$ with $|\alpha|<1$. u_{it} represents the unobserved disturbance term whereas η_i represents the individual-specific effects. The error components $\eta_i + u_{it}$ follow a white noise process such that $E[\eta_i] = 0, E[u_{it}] = 0$ and $E[\eta_i u_{it}] = 0$. Furthermore, $E[u_{is}u_{it}] = 0$ for $i = 1, .., N$ and $\forall t \neq s$.

The explanatory variable x_{it} also follows an autoregressive process of the following order

$$x_{it} = \rho x_{i,t-1} + \tau \eta_i + \theta u_{it} + e_{it}$$

for $i = 1, .., N$ and $t = 2, .., T$ with $|\rho|<1$. The unobserved error term e_{it} also follows a white noise process such that $E[e_{it}] = 0$ and $E[\eta_i e_{it}] = 0$.. The explanatory variable is correlated with the fixed effect η_i via the parameter τ and with the error term u_{it} via θ. The model specification also assumes normality of the unobserved error terms as well as the individual-specific fixed effects such that $u_i \sim \mathcal{N}(0;\sigma_u^2)$, $e_i \sim \mathcal{N}(0;\sigma_e^2)$ and $\eta_i \sim \mathcal{N}(0;\sigma_\eta^2)$.

Three cases of persistence are considered in the current study; $\alpha = \rho = 0$, $\alpha = \rho = 0.5$ and $\alpha = \rho = 0.9$ which represent zero, medium and high persistence. Furthermore, different values of N and T are used to understand the behaviour of the estimator under different scenarios; $N = 100, 400, 700$ and $T = 5, 12$ The values of the parameters are fixed as follows:

$$\beta = 1,\ \tau = 0.25,\ \theta = \text{-}0.1,\ \sigma_\eta^2 = 1,\ \sigma_u^2 = 1 \text{ and } \sigma_e^2 = 0.16$$

The explanatory variable has two sources of endogeneity: the fixed effects which impacts the steady states of both x_{it} and y_{it} as well as the error term. The negative value of θ counters the effect of the measurement error u_{it}. Initialisation of the dependent and explanatory variables along with its distribution are further explained in the Appendix. The data is simulated 1000 times, each time with different starting values. The parameters for each dataset are estimated using system-GMM with the same settings as are used to estimate the observed data.

Table 7 presents the results obtained from estimating the simulated data. The estimator is evaluated on the basis of root mean squared error (RMSE).[15] The main result from the table below suggests that system-GMM estimates the parameters α and β with the lowest bias in the case of high persistence i.e., $\alpha = \rho = 0.9$ for both $T = 5$ and $T = 12$. In the case of no persistence, increasing the time period from $T = 5$ to $T = 12$ reduces the bias by 21% and increases the efficiency by almost 50% in the estimation of α. Overall, as persistence in the dependent and explanatory variable increases, standard deviation of the estimator(s) decreases. For the cases of α=ρ=0.5, 0.9, there is no reduction in bias with an increase in T, however, the standard deviation of the parameter estimates reduces by almost 30% and 50% respectively. For all cases of T and persistence, there is an efficiency gain as the number of cross-sectional units N increases with no change in the bias of the estimated parameters. With respect to RMSE, it is clear that when the data is highly persistent, system-GMM estimators have the lowest bias as well as variance as compared to medium and zero persistent data, across both time periods.

The aim of the simulation exercise was to understand the behaviour of system-GMM estimates for different values of N, T, α and ρ. The data in the current study is observed for $N = 426$ and $T = 5$ with an estimated AR(1) term of 0.89. This closely corresponds to the simulated case of $N = 400$, $T = 5$ and $\alpha = 0.9$. From table 7, it is clear that the estimator of both α and β is least biased and more efficient in case of high persistence as compared to medium and no persistence which is also reflected from the value of RMSE of the estimator.

[15] RMSE is computed as the square root of the sum of squared bias and the variance of the estimator.

Table 7: Result of Monte Carlo simulation

	α			β		
$\alpha = \rho = 0$, T = 5	Bias	Sd	RMSE	Bias	Sd	RMSE
N = 100	0.189	0.098	0.213	0.618	0.150	0.637
N = 400	0.188	0.049	0.195	0.622	0.077	0.627
N = 700	0.188	0.036	0.195	0.622	0.059	0.625
$\alpha = \rho = 0.5$, T = 5						
N = 100	0.229	0.068	0.239	0.273	0.157	0.315
N = 400	0.236	0.033	0.238	0.268	0.076	0.28
N = 700	0.235	0.025	0.237	0.269	0.058	0.276
$\alpha = \rho = 0.9$, T = 5						
N = 100	0.029	0.013	0.032	0.069	0.133	0.149
N = 400	0.028	0.006	0.029	0.065	0.065	0.09
N = 700	0.028	0.004	0.029	0.068	0.048	0.083
$\alpha = \rho = 0$, T = 12						
N = 100	0.149	0.053	0.158	0.574	0.099	0.582
N = 400	0.148	0.030	0.151	0.568	0.060	0.571
N = 700	0.147	0.020	0.148	0.565	0.040	0.567
$\alpha = \rho = 0.5$, T = 12						
N = 100	0.229	0.068	0.239	0.273	0.157	0.315
N = 400	0.219	0.020	0.224	0.276	0.048	0.281
N = 700	0.221	0.015	0.211	0.276	0.036	0.279
$\alpha = \rho = 0.9$, T = 12						
N = 100	0.028	0.007	0.029	0.064	0.082	0.104
N = 400	0.028	0.003	0.028	0.066	0.039	0.077
N = 700	0.028	0.002	0.028	0.067	0.029	0.073

Note: The above table reports the bias, standard deviation and RMSE of the system-GMM estimator for parameters α and β for three cases of persistence wih different values of N and T. For each of the cases presented, estimator with the lowest value of RMSE is preferred.

9 Conclusion

In the current environment of low, sometimes negative interest rates, as well as in the absence of a unified banking market in Europe, the overall profitability and growth of the European banking industry is hampered. In this study, bank profitability is measured by net interest margin defined as the difference between interest income and interest expenditure as a ratio of interest bearing assets. The aim of the current research is to study the effect of annual bank-, industry- and country-specific data on the net interest margin of a sample of 426 domestic and foreign banks operating in 15 European countries over the period 2013-17.

Based on the existing literature, the effect of bank size, bank credit risk, operational efficiency, diversification, market concentration, inflation and non-performing loans on bank

NIM is estimated using system-GMM developed by Blundell and Bond (1998). The total sample is divided into two sub-samples of 297 domestic and 129 foreign banks. The highly significant AR(1) term is indicative of the concentration in the European banking market as well as the persistence of profits. Bank size is observed to have a strong negative effect on both domestic and foreign banks which is in line with the results obtained by Pasiouras and Kosmidou (2007) suggesting that economies of scale are enjoyed by smaller banks enhancing their profitability. It is in fact the variable with the largest impact on bank NIM irrespective of the ownership structure. Bank credit risk measured by the ratio of bank-level loan loss provisions to gross loans has a significant positive impact on the sub-sample sample of foreign banks. On the other hand, operational efficiency significantly negatively affects the NIM of foreign banks in the current sample which supports the result obtained by Pasiouras and Kosmidou (2007). Similarly, diversification measured by the ratio of non-interest income to operating revenue of the bank significantly negatively affects the NIM of both domestic and foreign banks. The result makes economic sense since a higher ratio of NII reflects the dependence of banks on income from non-traditional interest activities, reducing the net interest margin earned by them. Among the industry- and country-specific variables, the ratio of non-performing loans to gross loans in the economy has a significant negative effect on the entire sample of banks considered in the current study. This is in line with the expectation of the researcher, a higher ratio of NPL in the economy has a direct impact on bank profitability due to realised losses on its credit portfolio.

Overall, while the NIM of domestic banks are significantly impacted by bank size and diversification, foreign banks' NIM is additionally impacted by credit risk and operational efficiency. In the current sample, market concentration nor the inflation rate have a significant impact on the bank NIM, which could possibly be due to the short span of the sample period, within which the two factors do not vary much.

10 Discussion and future scope

Sustainable banking sector profitability is important for any economy since it ensures a stable financial system as well as protects the economy against potential losses from a poor credit portfolio. Furthermore, capital strength and profitability enhance the creditworthiness of banks which translates into lower funding costs for the bank as well as the overall industry. It ensures smooth flow of funds to profitable firms which further boosts economic growth and

productivity. The current study provides empirical evidence of the negative impact of bank size, cost inefficiency and diversified banking activities on net interest margin. The European banking industry is endowed with its fair share of challenges, both internal and external that impact its overall performance and profitability.

The European Central Bank has identified a few such factors; business model for instance, reflects the extent to which the bank depends upon income from the traditional interest bearing activities of lending (loans) and borrowing (deposits). Their analysis suggests that financial institutions engaging in activities such as asset management or investment banking are able to generate higher revenues than commercial banks relying solely on interest income.[16] Furthermore, in the current face of technological advancement banks also face increased competition from digitalisation of banking services by non-bank financial institutions. If adopted by banking firms especially those with a high number of physical branches, it could lead to a significant reduction in operating costs without losing their existing customer base and market share. Such an increase in cost efficiency will reflect in improved bank profitability. It is crucial that the technological shift in the banking industry is supported by the labour laws, market structure as well as the digital competence of the economy. Lastly, financial integration is a key factor that can boost the overall performance of the banking industry. While cross-border consolidation offers the benefit of diversified macroeconomic risks as well as increased consumer and market share in both the markets, consolidation within national borders is highly beneficial for small- and medium-sized firms as it enables them to increase their scale and scope of operation.[17]

The current study can be extended by including a more recent dataset extending beyond 2017. Furthermore, bank profitability can be alternatively be measured by either return on asset or return on equity. It would be interesting to study the effects of market interest rates as well as the slope of the yield curve on bank profitability in addition to the country-specific variables considered in this paper. The scope of the current research can also be geographically extended to other European countries as well as be made into a comparison between American and European banks.

[16] https://www.ecb.europa.eu/press/key/date/2018/html/ecb.sp181115_1.en.html
[17] https://www.ecb.europa.eu/press/key/date/2019/html/ecb.sp190501~7733ecc1a9.en.html

References

Albertazzi, U. and Gambacorta, L. (2009). Bank profitability and the business cycle. *Journal of Financial Stability*, 5:393–409.

Allen, L. (1988). The DeterminantsBank Interest Margins: A Note. *Journal of Financial and Quantitative Analysis*, 23:231–235.

Anderson, T. and Hsiao, C. (1982). Formulation and estimation of dynamic models using panel data. *Journal of Econometrics*, 18:47–82.

Angbazo, L. (1997). Commercial bank net interest margins, default risk, interest rate risk and off-balance sheet banking. *Journal of Banking and Finance*, 21:55–87.

Arellano, M. and Bond, S. (1991). Some tests of specification for panel data: Monte-Carlo evidence and an application to employment equations. *The Review of Economic Studies*, 58:277–297.

Athanasoglou, P. P., Brisimis, S. N., and Delis, M. D. (2008). Bank-specific, industry-specific and macroeconomic determinants of bank profitability. *Journal of International Financial Markets, Institutions and Money*, 18:121–136.

Berger, A., Demirguc-Kunt, A., Levine, R., and Haubrich, J. G. (2004). Bank concentration and competition: An evolution in the making. *Journal of Money, Credit, and Banking*, 36:433–451.

Berger, A. N., Deyoung, R., Genay, H., and Udell, G. F. (2000). Globalization of Financial Institutions: Evidence from cross-border banking performance. Technical report, Brookings-Wharton Papers on Financial Services.

Blundell, R. and Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, 87:115–143.

Blundell, R., Bond, S., and Windmeijer, F. (2000). Estimation in dynamic panel data models: improving on the performance of the standard GMM estimator. Technical Report W00/12, Institute for Fiscal Studies Working Paper, London.

Bourke, P. (1989). Concentration and other determinants of bank profitability in Europe, North America and Australia. *Journal of Banking and Finance*, 13:65–79.

Bouzgarroua, H., Jouida, S., and Louhichi, W. (2018). Bank profitability during and before the financial crisis: Domestic versus foreign banks. *Research in International Business and Finance*, 44:26–39.

Boyd, J. H., Levine, R., and Smith, B. D. (2001). The impact of inflation on financial sector performance. *Journal of Monetary Economics*, 47:221–248.

Claessens, S., Demirguc-Kunt, A., and Huizinga, H. (2001). How does foreign entry affect domestic banking markets. *Journal of Banking & Finance*, 25:891–911.

Claeys, S. and Vennet, R. V. (2008). Determinants of bank interest margins in Central and Eastern Europe: A comparison with the West. *Economic Systems*, 32:197–216.

de Guevara, J. F., Maudos, J., and Perez, F. (2005). Market power in European banking sectors. *Journal of Financial Services Research*, 27:109–137.

Demirguc-Kunt, A. and Huizinga, H. (1999). Determinants of commercial bank interest margins and profitability: some international evidence. *World Bank Economic Review*, 13:379–408.

Demirguc-Kunt, A. and Huizinga, H. (2010). Bank activity and funding strategies: The impact on risk and returns. *Journal of Financial Economics*, 98:626–650.

Demirguc-Kunt, A., Laeven, L., and Levine, R. (2003). Regulations, market structure, institutions and the cost of financial intermediation. Technical Report 9890, National Bureau of Economic Research Working Paper.

DeYoung, R. and Rice, T. (2004). Non-interest income and financial performance at U.S. commercial banks. *The Financial Review*, 39.

Dietrich, A. and Wanzenried, G. (2011). Determinants of bank profitability before and during the crisis: Evidence from Switzerland. *Journal of International Financial Markets, Institutions & Money*, 21:307–327.

Goddard, J., Molyneux, P., and Wilson, J. O. S. (2004). The profitability of European banks: a cross-sectional and dynamic panel analysis. Technical report, The Manchester School.

Goldberg, L. G. and Rai, A. (1996). The structure-performance relationship for European banking. *Journal of Banking & Finance*, 20:745–771.

Guru, B. K., Staunton, J., and Balashanmugam, B. (1999). Determinants of commercial bank profitability in Malaysia. 12th Annual Australian Finance and Banking Conference, Sydney, Australia.

Herrero, A. G., Gavila, S., and Santabarbara, D. (2009). What explains the low profitability of Chinese banks? *Journal of Banking & Finance*, 33:2080–2092.

Ho, T. S. Y. and Saunders, A. (1981). The Determinants of Bank Interest Margins:Theory and Empirical Evidence. *Journal of Financial and Quantitative Analysis*, 16:581–600.

K.Kosmidou, F.Pasiouras, C.Zopounidis, and M.Doumpos (2006). A multivariate analysis of the financial characteristics of foreign and domestic banks in the UK. *Omega*, 34:189–195.

Kosmidou, K. (2008). The determinants of banks' profits in Greece during the period of EU financial integration. *Managerial Finance*, 34:146–159.

Lakhani, K., Reid, J., and Templeman, L. (2019). How to fix european banking ... and why it matters. Technical report, Deutsche Bank.

Lee, C.-C., Yang, S.-J., and Chang, C.-H. (2014). Non-interest income, profitability, and risk in banking industry: A cross-country analysis. *North American Journal of Economics and Finance*, 27:48–67.

Lepetit, L., Nys, E., Rous, P., and Tarazi, A. (2008a). Bank income structure and risk: An empirical analysis of European banks. *Journal of Banking & Finance*, 32:1452–1467.

Lepetit, L., Nys, E., Rous, P., and Tarazi, A. (2008b). The expansion of services in European banking: Implications for loan pricing and interest margins. *Journal of Banking & Finance*, 32:2325–2335.

Maudos, J. and de Guevara, J. F. (2004). Factors explaining the interest margin in the banking sectors of the European Union. *Journal of Banking and Finance*, 28:2259–2281.

McShane, R. and Sharpe, I. (1985). A time series/cross section analysis of the determinants of Australian trading bank loan/deposit interest margins: 1962-1981. *Journal of Banking and Finance*, 9:115–136.

Molyneux, P. and Thornton, J. (1992). Determinants of European bank profitability: A note. *Journal of Banking & Finance*, 16.

Naceur, S. B. (2003). The Determinants of the Tunisian Banking Industry Profitability:Panel Evidence. Economic Research Forum(ERF) 10th Annual Conference, Marrakesh-Morocco.

Nguyen, J. (2012). The relationship between net interest margin and non-interest income using a system estimation approach. *Journal of Banking & Finance*, 36:2429–2437.

Pasiouras, F. and Kosmidou, K. (2007). Factors influencing the profitability of domestic and foreign commercial banks in the European Union. *Research in International Business and Finance*, 21:222–237.

P.Athanasoglou, P., N.Brissimisa, S., and D.Delis, M. (2008). Bank-specific, industry-specific and macroeconomic determinants of bank profitability. *Journal of International Financial Markets, Institutions and Money*, 18:12–136.

Perry, P. (1992). Do banks gain or lose from inflation? *Journal of Retail Banking*, 14:25–40.

Revell, J. (1979). Inflation and financial institutions. *Financial Times, London.*

Roodman, D. (2009a). How to do xtabond2: An introduction to difference and system GMM in stata. *The Stata Journal*, 9:86–136.

Roodman, D. (2009b). A note on the theme of too many instruments. *Oxford Bulletin of Economics and Statistics*, 71:135–158.

Saunders, A. and Schumacher, L. (2000). The determinants of bank interest rate margins: An international study. *Journal of International Money and Finance*, 19:813–832.

Short, B. (1979). The relation between commercial bank profit rates and banking concentration in Canada, Western Europe and Japan. *Journal of Banking and Finance*, 3:209–219.

Smirlock, M. (1985). Evidence on the (non) relationship between concentration and profitability in banking. *Journal of Money, Credit and Banking*, 17:69–83.

Soto, M. (2009). System GMM estimation with a small sample. Technical Report 395, Barcelona Economics Working Paper Series Working Paper.

Staikouras, C. K. and Wood, G. E. (2003). The determinants of bank profitability in Europe. *International Business & Economics Research Journal*, 3:57–68.

Stiroh, K. J. (2004). Diversification in banking: Is non-interest income the answer? *Journal of Money, Credit and Banking*, 36:853–882.

Sufian, F. and Habibullah, M. S. (2009). Bank specific and macroeconomic determinants of bank profitability: Empirical evidence from the China banking sector. *Frontiers of Economics in China*, pages 274–291.

Valverde, S. C. and Fernandez, F. R. (2007). The determinants of bank margins in European banking. *Journal of Banking & Finance*, 31:2043–2063.

Williams, B. (2003). Domestic and international determinants of bank profits: Foreign banks in Australia. *Journal of Banking & Finance*, 27:1185–1210.

Williams, B. (2007). Factors determining Net Interest Margins in Australia: Domestic and Foreign banks. *Financial Markets, Institutions & Instruments*, pages 145–165.

11 Appendix

Additional results

Table 8: Estimated system-GMM coefficients for the entire bank sample, domestic and foreign banks

	Dependent variable: NIM		
	All banks	Domestic banks	Foreign banks
NIM_{t-1}	0.919***	0.929***	0.871***
	(0.065)	(0.138)	(0.079)
Bank size	−0.299**	−0.261	−0.251
	(0.139)	(0.196)	(0.416)
Bank credit risk	0.045**	0.038	0.052*
	(0.021)	(0.029)	(0.030)
Operational efficiency	−0.003***	−0.003***	−0.002
	(0.001)	(0.001)	(0.002)
Capital strength	0.032*	0.063**	0.022
	(0.018)	(0.032)	(0.016)
Liquidity	−0.001	0.0005	−0.004**
	(0.002)	(0.004)	(0.002)
Diversification	−0.013***	−0.009***	−0.011*
	(0.003)	(0.003)	(0.006)
Market concentration	−0.0002	−0.00002	−0.001**
	(0.0001)	(0.0001)	(0.001)
GDP	−0.008	−0.008	−0.012
	(0.007)	(0.007)	(0.015)
Inflation	−0.019	−0.002	−0.028
	(0.014)	(0.018)	(0.030)
Non-performing loans	−0.015	−0.012	−0.020
	(0.011)	(0.015)	(0.028)
Domestic credit	−0.002	−0.006	0.005
	(0.005)	(0.005)	(0.007)
Observations	426	297	129
Sargan test	0.113	0.255	0.364
AB test AR(1)	0.0003	0.0017	0.0315
AB test AR(2)	0.583	0.374	0.286
Wald test $\chi^2(23)$	39605.43	18574	14742.85

Note: The above table reports the coefficients estimated by applying system-GMM on the entire sample of 426 banks, 297 domestic and 129 foreign banks. The dependent variable is net interest margin of the banks. The explanatory variables include bank-, industry- and country-specific variables. The sample period ranges from 2013-17. Coefficients marked with ***, ** and * indicate that their p-value is lesser than 0.01, 0.05 and 0.10 respectively. The standard errors in the parenthesis are auto-correlation and heteroskedasticity robust. Critical value of $\chi^2(23)$ is 35.172 at 5% significance level.

Table 9: Result of pooled OLS, fixed and random effects on the entire sample of banks

	Dependent variable: NIM		
	Pooled OLS	Fixed effects	Random effects
Bank size	-0.231^{***}	-0.545^{***}	-0.316^{***}
	(0.005)	(0.094)	(0.031)
Operational efficiency	-0.003^{***}	-0.005^{***}	-0.004^{***}
	(0.001)	(0.001)	(0.001)
Diversification	-0.011^{***}	-0.016^{***}	-0.015^{***}
	(0.001)	(0.003)	(0.002)
Bank credit risk	0.117^{***}	0.029^{***}	0.032^{***}
	(0.007)	(0.002)	(0.004)
Market concentration	0.0001	-0.0001	0.00004
	(0.0001)	(0.0001)	(0.0001)
Inflation	-0.106^{***}	-0.052^{***}	-0.055^{***}
	(0.019)	(0.005)	(0.008)
Non-performing loans	0.001	0.002	0.001
	(0.003)	(0.001)	(0.002)
Constant	4.421^{***}		5.384^{***}
	(0.092)		(0.390)
Observations	426	426	426
R squared	0.178	0.204	0.184
Wald test $\chi^2(8)$	461.34	435.94	479.29

Note: The above table reports the coefficients estimated by applying pooled OLS, fixed effects and random effects on the entire sample of 426 banks The dependent variable is net interest margin of the banks. The explanatory variables include bank-, industry- and country-specific variables. The sample period ranges from 2013-17. Coefficients marked with ***, ** and * indicate that their p-value is lesser than 0.01, 0.05 and 0.10 respectively. The standard errors in the parenthesis are cluster robst. Critical value of $\chi^2(7)$ is 14.067 at 5% significance level.

Table 10: Coefficient of correlation among the dependent and explanatory variables

	A	B	C	D	E	F	G	H	I	J	K	L
A: NIM		**-0.31**	**0.27**	**-0.06**	**0.19**	**-0.08**	**-0.19**	-0.02	-0.04	**-0.04**	0.02	-0.00
B: Bank size	**-0.41**		**-0.40**	**-0.16**	**-0.07**	**-0.05**	**-0.09**	-0.02	**-0.08**	**0.11**	**-0.08**	**0.18**
C: Capital strength	**0.40**	**-0.47**		0.03	-0.03	**0.46**	**0.11**	-0.03	0.02	**0.04**	-0.02	**-0.06**
D: Operational efficiency	-0.01	**-0.18**	-0.01		-0.03	**0.08**	**0.21**	**0.05**	**0.08**	-0.04	-0.02	**-0.10**
E: Bank credit risk	**0.28**	-0.02	0.02	**-0.08**		**0.04**	-0.01	-0.02	-0.04	**-0.10**	**0.09**	**0.05**
F: Liquidity	**-0.16**	-0.03	**0.13**	**0.11**	0.02		**0.13**	0.02	**0.11**	**0.06**	-0.03	**-0.05**
G: Diversification	**-0.25**	-0.03	**0.14**	**0.21**	**0.10**	**0.21**		**0.09**	0.02	**-0.08**	**0.07**	**-0.09**
H: Domestic credit	**-0.07**	**0.04**	-0.03	0.02	**-0.08**	**0.11**	**0.08**		**0.05**	**-0.35**	**0.21**	**-0.10**
I: Inflation	-0.03	**-0.09**	0.03	**0.10**	**-0.06**	**0.11**	-0.03	0.03		**-0.13**	**0.04**	**-0.11**
J: GDP	**-0.12**	**0.09**	**0.11**	-0.03	**-0.30**	**0.09**	**-0.08**	0.00	-0.01		**-0.58**	-0.01
K: Non-performing loans	-0.02	**-0.05**	-0.02	**-0.08**	**0.10**	-0.01	**0.10**	**0.10**	**0.06**	**-0.47**		-0.00
L: Market concentration	-0.03	**0.21**	**-0.07**	**-0.19**	**0.10**	-0.02	0.03	**-0.10**	**-0.29**	-0.04	**-0.09**	

Note: The table reports Pearson correlations above and Spearman correlations below the diagonal between the bank-, industry and country-specific variables. Correlations with significance levels below 5% appear in bold print.

Monte Carlo Simulation

It is easier to express x_{it} and y_{it} as deviations from their steady states:

$$x_{it} = \frac{\tau\eta_i}{1-\rho} + \xi_{it}$$

where, ξ_{it} represents the deviation from the steady state equal to

$$\xi_{it} \equiv (1-\rho L)^{-1}(\theta u_{it} + e_{it}) \ ^{18}$$

$$= \theta p_{it} + q_{it}$$

which is a sum of two independent AR(1) processes p_{it} and q_{it} with variances:

$$\sigma_p^2 = \frac{\sigma_u^2}{1-\rho^2} \quad \text{and} \quad \sigma_q^2 = \frac{\sigma_e^2}{1-\rho^2}$$

Based on independent variables η, u_1 and e_1, x_{it} can be initialised as

$$x_{i1} = \frac{\tau\eta}{1-\rho} + [\theta u_{i1} + e_{i1}](1-\rho^2)^{-0.5}$$

Similarly, $y_{it} = \frac{\eta_i}{1-\alpha} + \beta(1-\alpha L)^{-1}x_{it} + (1-\alpha L)^{-1}u_{it}$

Substituting the value of x_{it} in the above expression gives

$$y_{it} = \frac{1-\rho+\beta\tau}{(1-\alpha)(1-\rho)}\eta_i + \zeta_{it}$$

where, ζ_{it} represents the deviation from the steady state equal to

$$\zeta_{it} \equiv \beta(1-\alpha L)^{-1}(1-\rho L)^{-1}[\theta u_{it} + e_{it}] + (1-\alpha L)^{-1}u_{it} = \beta\theta r_i t + \beta s_{it} + v_{it}$$

where

$$r_t = \phi_1 r_{t-1} + \phi_2 r_{t-2} + u_t \ s_t = \phi_1 s_{t-1} + \phi_2 s_{t-2} + e_t \ v_t = \alpha v_{t-1} + u_t$$

which is a sum of two independent AR(2) processes and one AR(1) process with autoregressive parameters $\phi_1 = \alpha + \rho$ and $\phi_2 = -\alpha\rho$. The associated variances are as follows:

$$\sigma_r^2 = \frac{\sigma_u^2(1-\phi_2}{[(1+\phi_2)((1-\phi_2)^2-\phi_1^2]} \ \sigma_s^2 = \frac{\sigma_e^2(1-\phi_2}{[(1+\phi_2)((1-\phi_2)^2-\phi_1^2]} \ \sigma_v^2 = \frac{\sigma_u^2}{1-\alpha^2}$$

Given these variances, it is possible to draw mean and variance stationary observations of r_t, s_t and v_t. Thus, the process y_t can be initialised as

[18] L is the lag operator; for any variable v_{it} and parameter γ, $(1-\gamma L)^{-1}v_{it}$ is defined as $(1-\gamma L)^{-1}v_{it} \equiv v_{it} + \gamma v_{i,t-1} + \gamma^2 v_{i,t-2}$

$y_1 = \frac{1-\rho+\beta\tau}{(1-\rho)(1-\alpha)}\eta + \beta\theta r_1 + \beta s_1 + v_1$

A burn-in of 50 time-periods is used in the simulaiton process since the above expression does not ensure covariance stationarity of the initial observations.