Argumenta Oeconomica
Year 2025, Vol. 55, No. 2
ISSN 2720-5088
journals.ue.wroc.pl/aoe

Market power in the EU banking sector in a time of unconventional monetary policy

Cristina Ortega

Universidad Autónoma de Madrid, Spain

e-mail: cristina.ortegag@uam.es

ORCID: 0009-0005-1731-7164

Quote as: Ortega, C. (2025). Market power in the EU banking sector in a time of unconventional monetary policy. *Argumenta Oeconomica*, *2*(55), 181-203.

DOI: 10.15611/aoe.2025.2.12

JEL: L11, D22, G21, G28

Abstract

Aim: This paper investigates how market power has evolved in the EU banking sector during a period of unconventional monetary policy, particularly under negative interest rates.

Methodology: The author estimated an adjusted Lerner index through stochastic frontier analysis applied to an unbalanced panel of 272 EU commercial banks from 2015 to 2019, accounting for contextual factors including monetary policy stance, financial system development and regulatory environment.

Results: The findings show that the traditional Lerner index overstated market power in EMU countries due to near-zero interest rates. The adjusted index reveals lower market power in EMU banks and consistently higher levels in non-EMU countries, especially the UK and the Nordic countries.

Implications and recommendations: The findings emphasise the need to consider monetary policy and institutional factors in competition analysis. Future research should explore how banks adjust pricing under persistent low-rate environments.

Originality/value: This paper offers a refined measure of bank market power that corrects for biases in standard metrics during periods of unconventional monetary policy, enhancing cross-country comparability within the EU.

Keywords: market power, stochastic frontier, Lerner index, banking

1. Introduction

Banking competition in the European Union (EU) has evolved since the introduction of the 1992 single market programme (SMP), which initiated the course towards a financial market integration in the European Union (EU)[1]. The objective of achieving a more integrated financial system emerged from the notable increase in cross-border financial activity among EU countries, prompted by the financial deregulation process and technological advances since the 1980s. Starting from 2012, coinciding with the announcement of the ECB outright monetary transactions (OMT) programme and the first steps taken toward the EU Banking Union (EBU)[2], further integration of the banking sector has been witnessed. At present, despite advances in the banking union through the establishment of a single supervisory mechanism (SSM) and a single resolution mechanism (SRM), cross-border integration in the banking industry remains low. According to Cruz-García et al. (2017), this fact proves the lack of cross-border mergers within euro area banks and shows that European banking markets remain nationally based (Maudos, & Vives, 2019).

The integration of the EBU aims to create a level playing field, ensuring that financial institutions across EU member states operate under similar conditions. Additionally, advances in the EBU would lead to lower compliance, resolution and restructuring costs, the elimination of barriers to cross-border banking activity and eventually lower bank funding costs (Goyal et al., 2013). For these reasons, one expects that the harmonisation of financial conditions is likely to promote increased competition among banks operating in the EU.

However, since the introduction of the euro in 1999, De Jonghe et al. (2016) described a general trend of competition deterioration in the EU. Moreover, Delis and Tsionas (2009) found significant variability between EU countries in banking market power, probably as a consequence of barriers to integration. According to the ECB (2018), litigation costs, as well as divergences in legal and regulatory frameworks, constitute elements of the regulatory environment that may lead to different competition scenarios within the EU. Additionally, in the aftermath of the global financial crisis (GFC), many EU countries initiated a consolidation path through mergers and acquisitions (M&As), which could have contributed to a rise in banking market power.

This study aimed to shed light on the present EU banking competition scenario and to assess whether there are significant market power differences between eurozone (EMU) and non-eurozone (non-EMU) countries. As suggested above, the context in which banks operate seems to influence their capacity to exercise market power, therefore this study aimed to assess the market power of EU banks while controlling for the market environment in which they operate. The author examined this by estimating an adjusted-Lerner index for all EU countries from 2015 to 2019 and comparing them to the traditional Lerner index estimations. To achieve this, an empirical model was developed, based on the stochastic frontier model of market power in Kumbhakar et al. (2012), which allows for the inclusion of exogenous variables to control for the market environment.

First, a key variable shaping the banking market context is monetary policy. The literature suggests that short-term market interest rates systematically influence banks' margins, thereby potentially affecting banking market power. Igan et al. (2021) found that the traditional Lerner index becomes uninformative as an indicator of market power in a context of close to or below zero interest rates. The Lerner index increases if the ratio of interest paid on deposits (R_d to the interest earned on assets (R_a) decreases (given that $Lerner = 1 - \varepsilon \cdot \frac{R_d}{R_a}$, where ε is the elasticity of costs to quantity). Therefore, when short-term interest rates fall towards zero in a context of lax monetary policy, these

---

1 Three features characterise fully integrated financial markets: (i) the existence of a single set of financial rules, (ii) the guarantee of equal access to financial instruments and services for all market participants, and (iii) the existence of harmonised procedures that permit equal treatment of users of financial services (ECB, 2018).

2 The European Banking Union (EBU) is set up under three pillars: the single supervisory mechanism (SSM), the single resolution mechanism (SRM), and the harmonised regulation of deposits insurance.

put pressure on the net interest margin (NIM) of banks, lowering their profits, yet the Lerner index would artificially rise to one, mistakenly indicating higher market power. The authors of that study warn that this could be one potential explanation behind the increase in the Lerner index for many advanced economies in the aftermath of the global financial crisis (GFC). In fact, bank interest income and expenses have declined following the drop in policy interest rates, explaining why NIMs have remained flat, hence it is important to investigate how changes in the policy interest rate may have influenced banks' market power in the setting of a negative interest rate policy (NIRP).

The objective of negative policy rates is to boost the economy. One of the channels through which monetary policy affects the real economy is the lending channel. In this context, commercial banks are incentivised to hold fewer reserves at the central bank, stimulating growth of bank lending, and this would translate into lower interest rates on loans, making borrowing cheaper for businesses and consumers. However, negative rates squeeze net interest margins (Claessens et al., 2018), as increased competition for lending leads to lower loan rates, while interest on deposits remains unchanged, as these tend to be rigid with respect to monetary policy changes (Hannan, & Berger, 1997; Gambacorta, & Iannotti, 2007). This situation may push banks to focus on more diversified revenue sources to compensate for the lack of income from traditional lending activities (Altavilla et al., 2024), thereby increasing non-interest income. As Altunbas et al. (2023) pointed out, the increase in market power in the NIRP environment could be achieved through higher fees or by increasing switching costs on deposits, making it more difficult for customers to switch to another bank.

Whether a shift towards non-interest income leads to more market power remains an empirical question – for instance, for small banks, generating non-interest revenue may be challenging (Claessens et al., 2018). On the other hand, since the business model of small banks is based on relationship lending (Degryse, & Van Cayseele, 2000), borrowers in these institutions tend to have fewer credit alternatives, which would give small banks the opportunity to leverage their position and increase market power. Furthermore, customer inertia, influenced by switching costs and limited awareness of market conditions, could amplify this dynamic (Berger et al., 2022).

Thus this paper aimed to empirically unravel the impact of negative interest rates on market power, while also considering how various bank characteristics, such as size and risk, and other market conditions, may affect the results.

Following Tan and Floros (2012) and Tan (2016), the adjusted Lerner index estimation included two industry factors that are known to affect banks' performance: (i) an indicator of market structure, given that the structure-conduct-performance hypothesis (SCP) argues that higher concentration levels may translate into higher market power (Hannan, 1991), and (ii) an indicator of the development of the financial system, since more developed banking sectors are positively related to higher bank profitability (Tan, & Floros, 2012). The estimation also includes capital regulation as an additional constraint since the banking literature recognises its influence on banking profitability (Lee, & Hsieh, 2013) and competition (Hakenes, & Schnabel, 2011).

The estimated results suggest that the adjusted Lerner index was levelled down for the whole sample of EU banks compared to traditional Lerner estimates. This finding supports the view that, in the context of negative policy rates that characterise the period of study (2015-2019), the traditional Lerner index is not informative, therefore the adjusted-Lerner estimates provided a more accurate assessment of the current competition scenario. Moreover, the estimation results suggest that non-EMU banks have enjoyed, on average, higher levels of market power for the whole period of study compared to banks in the eurozone. Among non-EMU countries, Central-Eastern European countries such as Czechia, Estonia, Hungary, Latvia and Poland seem to converge with the market power trend in EMU countries, whereas Nordic countries along with the UK appear to diverge from the eurozone competition levels, presenting the highest levels of market power within the European banking market.

The paper is organized as follows: Section 2 reviews the literature on the effect of the banking environment on competition. Section 3 focuses on the model and the econometric methodology employed. Then, Section 4 reports the data employed. Section 5 presents the empirical model specification and the estimation results, and finally Section 6 summarises the main conclusions.

2. Literature review

The literature on banking market power has evolved significantly in recent years, with various studies examining the factors that influence banks' ability to exercise market power and the implications for competition and economic efficiency. A notable contribution to this field is the work of Altunbas et al. (2023) which investigated the impact of negative monetary policy rates on the competitive behaviour of euro area banks. The study found that the introduction of negative interest rates led to increased market power, influencing both their lending behaviour and risk-taking. Fare et al. (2024) provided an in-depth theoretical framework for measuring market power using Lerner indices, incorporating firm inefficiency and price markups to assess the impact of market power on economic efficiency in various sectors, including banking. Additionally, Chaffai and Coccorese (2023) explored the determinants of banking market power in MENA countries, highlighting the role of customer switching costs and cost efficiency in shaping market power, particularly in more concentrated banking markets.

This paper contributes to the existing literature on banking competition in three key areas. Firstly, it employed an adjusted Lerner index, accounting for the influence of monetary policy and other market conditions. The study incorporated new contextual factors not included in previous studies, such as the effect of branch density (FIA) and the impact of capital requirements. Finally, the author investigated potential differences in market power levels across various bank clusters: EMU banks, Central-Eastern European banks, UK banks, and Nordic banks. By considering these factors, this study contributes to a more comprehensive understanding of the determinants of market power in the EU banking sector.

Monetary policy constitutes a common object of study in the banking performance literature. Most studies indicated a positive relation between short-term interest rates and banks' margins (Bolt et al., 2012; Borio et al., 2017; and Claessens et al., 2018; Igan, et al., 2021). Toolsema (2004) provided a theoretical model in which policy rates directly affect banks' marginal cost, altering their ability to charge a lending rate above the Central Bank's policy interest rate, showing that when the policy rate rises, market power (measured by the Lerner index) decreases. However, Alessandri and Nelson (2012) and Busch and Memmel (2015) indicated different implications depending on the time horizon considered. Since assets usually present longer maturity than liabilities, the portion of adjusted liabilities to the new short-term rates will be higher than the fraction of adjusted assets. This issue, along with differences in the association of the rates of each financial product to the market interest rates, may lead to worsening margins in the short run.

Nonetheless, in the context of NIRP, negative rates squeeze net interest margins (NIMs) due to heightened competition, while deposit rates remain rigid, prompting banks to seek non-interest revenue. Whether this leads to increased market power remains an empirical question and the final outcome is probably influenced by banks' characteristics. This study explores how these effects may vary based on factors such as bank size and risk.

Regarding the effect of market structure, the structure-conduct-performance (SCP) paradigm proposes that market concentration conditions banks' competitive conduct (see Mason, 1939; Bain, 1951)), however a clear direction of causality from structure to conduct has not yet been confirmed (Vesala, 1995). In fact a considerable number of authors in this field have identified structure measures as inadequate proxies for competition (Berger et al., 2004, 2009; Bikker, & Spierdijk, 2009; Bolt, & Humphrey, 2015). In this regard, Boone (2008) argued that a firm-specific measure of competition would be more appropriate since concentration measures do not consider firms' individual ability to alter markups on prices, and more concentrated banking markets and intense competition may not be incompatible under certain circumstances. Baumol's theory of contestable markets (Baumol, 1982) suggests that even in concentrated banking markets, banks may still behave competitively in the absence of sufficient barriers to entry for potential competitors.

Although concentration indicators may not be adequate proxies to directly infer competition, they provide significant industry-specific information on banking markets. In the context of the EU, market concentration has increased since 1997. Nonetheless, as pointed out by Maudos and Vives (2019), this constitutes a general trend and may mask significant differences in the evolution of banking market concentration among EU countries[3]. Therefore, given potential divergences between EMU and non-EMU countries in banking concentration trends, controlling for the banking structure is meaningful. This study includes the Herfindahl-Hirschman index (HHI) of total deposits as an indicator of market structure.

Another industry-specific determinant of bank performance is the development of the financial system. Most of the literature on financial development uses proxies such as the level of financial depth or access, however the term 'financial development' has a broader significance. Levine (2005) noted that developed financial institutions efficiently allocate capital, pool savings, screen borrowers, adequately monitor investments, and properly diversify risks. Moreover, according to Čihák et al. (2012), financial development also occurs when financial intermediaries mitigate the effects of imperfect information, limited enforcement and transaction costs. Čihák et al. (2012) further developed a multidimensional approach for assessing financial development, considering four characteristics of financial systems: depth, access, efficiency and stability.

Many studies analysed the relation between financial depth/access and banking competition. Love and Martínez Pería (2015) empirically showed that increased market power limits the access to credit by firms. Wang et al. (2020) also provided supporting evidence that bank market power imposes obstacles to SMEs' access to finance and boosts their credit constraints. Furthermore, Tan and Floros (2012) pointed out that more developed banking institutions increase the demand for banking services, which incentivises competition by attracting new entrants, yet Tan (2016) suggested that both the development of the banking sector and the stock market affect banks' performance, allowing for higher margins.

Finally, another industry-specific factor influencing banks' performance is capital regulation. Regarding the relation between capital regulation and banking competition, Hakenes and Schnabel (2011) argued that higher capital requirements inhibit competition for loans, prompting an increase in loan rates. Angelini and Cetorelli (2003) examined the impact of the Second Banking Directive (SBD) on the Lerner index for a sample of Italian banks, showing that markups were negatively influenced by the deregulation process initiated with the SBD. Fonseca and González (2010) pointed out that when banks enjoy monopoly power, bank shareholders may prefer to obtain funds by issuing equity rather than obtaining cheaper funding from deposits with the aim of maintaining the high charter value of their market power. Carvallo and Ortiz (2018) argued that large banks that enjoy higher market power are more prone to protect their charter value by holding higher levels of capital. Their results showed that banking markets with lower competition levels tended to have higher capital buffers.

3. Methodology

The model specification in this study is based on the method developed by Kumbhakar et al. (2012) intended to estimate firm-level market power. Tsionas et al. (2018) employed it in a system of two nonlinear equations to jointly estimate banks' efficiency and market power. The author applied this methodology as a reference basis and extended it by including contextual variables with the model specification of Battese and Coelli (1995).

The model of Kumbhakar et al. (2012) provides clear advantages over other frequently used market power estimation methods as it allows for the estimation of market power when input price data are not available. Moreover, it does not require information on output price necessary for calculations of the traditional Lerner index as data on total revenue are sufficient. Furthermore, no premise is needed regarding the existence of constant returns to scale as when following other New Empirical Industrial Organization (NEIO)methods (Bresnahan, 1989) or computing the traditional Lerner index.

The Kumbhakar et al. (2012) model starts with the assumption of some degree of market power for profit-maximising companies, thus the output price (P) that they set must be higher than the marginal cost (MC)

[3] Market concentration (calculated by bank total assets) increased in most EU countries from 1997 to 2017 except for Austria, Hungary, Czechia, Denmark, Finland and Slovenia.

$$P > MC \equiv \frac{\partial C}{\partial Y}. \quad (1)$$

Multiplying both sides of equation (1) by the ratio of output (*Y*) to total cost (*C*) results in

$$P\frac{Y}{C} = \frac{TR}{C} > MC\frac{Y}{C} = \frac{\partial C}{\partial Y}\frac{Y}{C} = \frac{\partial lnC}{\partial lnY}, \quad (2)$$

where (*TR/C*) is the total revenue share in total cost and $(\partial lnC/\partial lnY)$ is the cost-output elasticity.

A firm's cost-output elasticity varies depending on the technology employed. Regarding the banking industry, a bank's technology can be represented by the following translog total cost function

$$ln\,C = \beta_0 + \sum_{j=1}^{J}\beta_j lnW_j + 0.5\sum_{j=1}^{J}\sum_{k=1}^{K}\beta_{jk} lnW_j\,ln\,W_k + \beta_Y lnY + 0.5\beta_{YY}(lnY)^2 \ldots$$
$$+\textstyle\sum_{j=1}^{J}\beta_{Jy} lnW_j\,ln\,Y, \quad (3)$$

where *C* is the total cost, *Y* is the total production of financial assets, and W_j is the input employed in the production process (*j* = 1, 2, 3, i.e. labour, physical capital and deposits).

Thus cost-output elasticity $(\partial lnC/\partial lnY)$ is equal to

$$\frac{\partial lnC}{\partial lnY} = \beta_Y + \beta_{YY} lnY + \textstyle\sum_{j=1}^{J}\beta_{jY} lnW_j. \quad (4)$$

Accordingly, inequality (2) can be converted into an equality by adding a non-negative one-sided term $u \geq 0$:

$$\frac{TR}{C} = \frac{\partial lnC}{\partial lnY} + u. \quad (5)$$

By including a two-sided noise disturbance term v, and developing the cost elasticity term, equation (5) results in the following stochastic frontier function (also assuming homogeneity of dree 1 in the price of inputs):

$$\frac{TR}{C} = \frac{\partial lnC}{\partial lnY} + u + v = \beta_Y + \beta_{YY} lnY + \textstyle\sum_{j=1}^{J-1}\beta_{jY} lnW_j + u + v. \quad (6)$$

Note that since the term u represents the deviations of the revenue share to total cost from its frontier, and given that (5) is derived from (1), obtaining a measure of market power by estimating either the distance between the output price and the marginal cost or the distance between the total revenue share in the total cost $\left(\frac{TR}{C}\right)$ and its frontier $\left(\frac{\partial lnC}{\partial lnY} + v\right)$ is indifferent. A clear advantage of this method is that if the focus is to estimate markups, the complete total cost function (3) does not need to be estimated, and one can estimate (6). Therefore this alternative approach allows to obtain markup estimates directly from the estimation of equation (6).

Following the stochastic frontier fundamentals, the right-side term $\left(\frac{\partial lnC}{\partial lnY} + v\right)$ constitutes the frontier itself, where $\left(\frac{\partial lnC}{\partial lnY}\right)$ is the deterministic component and *v* the stochastic term. The non-negative one-sided term u measures the positive deviations from the frontier and constitutes the immediate proxy for markup. In the stochastic cost frontier literature, this term is considered *inefficiency*. However, given that within this specification one is dealing with the ratio of total revenue share to total cost $\left(\frac{TR}{C}\right)$ and not the single-variable total cost (C), u is interpreted only as a proxy for markup. Together, $u + v$ conforms to the so-called composite or term.

The estimation procedure continues with the estimation of the parameters in (6) by employing the maximum likelihood (ML) method which requires distributional assumptions for both u and v. Given that the one-sided error term u shows deviations from the frontier, it must be higher than zero $u \geq 0$, thus it cannot be normally distributed. Following the literature, Kumbhakar et al. (2012) considered a half-normal truncated at zero distribution for u and a normal distribution for the random noise component *v*:

$$u \sim N^{+}(0,\ \sigma_u^2), \tag{7}$$

$$v \sim N\ (0,\ \sigma_v^2). \tag{8}$$

After obtaining the ML estimates of β and u in (6), the 'markup factor' can be estimated θ. If the markup is defined by the price distance to marginal cost, then θ is

$$\theta = \frac{P-MC}{MC}\ . \tag{9}$$

After some calculations combining (7) and (9), the above specification of markup θ can be related to u as follows:

$$\theta = \frac{u}{\frac{\partial lnC}{\partial lnY}}\ . \tag{10}$$

Thus after estimating (6), markup factor ϑ can be obtained from:

$$\hat{\theta} = \hat{u}/\left(\sum_{j=1}^{J-1} \hat{\beta}_{jY}\, ln\widetilde{W}_j + \hat{\beta}_{YE} E + \hat{\beta}_Y\ + \hat{\beta}_{YY}\, ln\, Y\right). \tag{11}$$

Equation (11) shows that markup factor θ depends on the estimates of u and on the cost-output elasticity estimates. As pointed out by Kumbhakar et al. (2012), the value of $\hat{\theta}$ is mostly influenced by the value of $\hat{u}$, given that the estimated cost elasticity will not be far from unity. After obtaining $\hat{\theta}$, this value can then be employed to obtain the Lerner index *L* from the following relationship:

$$L = \frac{\hat{\theta}}{(1+\hat{\theta})}\ . \tag{12}$$

Therefore the aim was to obtain a bank-level value of $\hat{\theta}$ following the above methodology while incorporating the effects of the selected contextual variables, which then affects the estimation of u. According to the literature, a few main procedures can be employed to include the effect of exogenous variables in a stochastic frontier estimation. One of those is to assume that the contextual variables are likely to affect the distribution of the one-sided error term. According to Belotti et al. (2013), they can be incorporated employing three different alternatives: (i) shifting the frontier and the one-sided error distribution, (ii) scaling the frontier and the one-sided error distribution, and iii) shifting and scaling both the frontier and the one-sided error distribution.

In addition to the choice of how these exogenous variables may be included in the model, two important econometric issues must be considered. First, whether one may assume heteroskedasticity in the composite error term. In this regard, Kumbhakar and Tsionas (2008) pointed out that given that the banking industry comprises a considerable number of small entities and assets are predominantly concentrated in a few large banks, the variability of both error components is probably different across units, hence the most appropriate assumption is the presence of heteroskedasticity in u_i and v_i. According to Kumbhakar and Lovell (2000), neglecting heterogeneity in *v* does not generate bias for the frontier's parameter estimates, although it produces biased estimates of u. A second issue to consider is how to deal with the time dimension on the one-sided error component. Traditionally, in the stochastic cost frontier literature two possible approaches are suggested: either to consider time-varying or time-invariant technical inefficiency. From the time length of this study's dataset, time-varying u_{it} seems to be the most convenient choice.

Another additional concern is the model specification and estimation procedures. Pitt and Lee (1981) and Kalirajan (1981) first introduced the possibility of including explicative variables that affect the technical inefficiency term in stochastic frontier production functions, which is the immediate proxy for markup u in this model. These and other studies often employed a two-stage estimation method: first estimating the stochastic frontier model and the technical inefficiency level for each firm, and then analysing how the estimated inefficiency is affected by the exogenous variables. However, as demonstrated by Wang and Schmidt (2002), the two-stage procedure generates biased results given that the model initially estimated would not be correctly specified. They pointed out that the severity of the bias would depend on the level of correlation between the independent variables included in the frontier estimation (first step) and the set of exogenous variables included in the second step. In this context, (Kumbhakar et al., 1991) argued that in terms of stochastic production functions, inconsistent estimates of the parameters are obtained if a two-step estimation approach is employed when technical inefficiency u is correlated with the inputs. A suitable alternative consists of simultaneous estimation of the frontier and of the one-sided error term. In the case of panel data analysis, a variety of models follow this simultaneous approach[4].

In this regard, Battese and Coelli (1995) proposed a model specification for panel data that can be applied to the estimation of equation (6), using simultaneous estimation of the stochastic frontier equation and the term u, which permits the introduction of z explanatory variables (contextual variables):

$$\frac{TR}{C} = \beta_Y + \beta_{YY} lnY_{it} + \sum_{j=1}^{J-1} \beta_{jYt} lnW_{jt} + u_{it} + v_{it}. \quad (13)$$

$$u_{it} = z'_{it}\,\delta + \varepsilon_{it}, \quad (14)$$

where v_i follows a normal distribution

$$v_{it} \sim N\,(0,\, \sigma_v^2) \quad (15)$$

and u_i has a truncated-normal distribution (at zero), where $(z_i^{'}\,\delta$ is the parameterisation of the mean distribution of u, (z_i) is the vector of contextual variables and (δ) is the vector of z parameters:

$$u_{it} \sim N^{+}\big(z_{it}^{'}\,\delta,\, \sigma_{u_{it}}^2\big), \quad (16)$$

$$\mu_i = z_{it}^{'}\,\delta \quad (17)$$

is parameterisation of the mean of u allowed to analyse how this mean changes with variations in the values of the contextual variables. Thus ε_{it} is a random disturbance that follows a truncated normal distribution with zero mean and variance σ^2:

$$\varepsilon_i \sim N^{+}(0,\, \sigma^2\,). \quad (18)$$

Hence this equation system is employed to obtain ML estimates of both technological and contextual parameters.

4. Data and variables

4.1. Database

This study employed an unbalanced panel dataset of EU-28 banks spanning the period 2015-2019, selected given that it was characterised by sustained emic growth following the end of the euro area sovereign debt crisis (SDC) and preceding the COVID-19 pandemic. This timeframe was marked by low interest rates and excess liquidity in the EU, largely due to near-zero or negative interest rates and significant asset purchases by EU central banks. While the period may seem short, similar studies, such as those by Acharya et al. (2021) and Bassett et al. (2020) also focused on relatively brief periods around major crises, including the global financial crisis (GFC) and euro area crisis. The euro area SDC, which occurred primarily between 2009 and 2015, involved financial instability, particularly in Greece, Ireland, and Spain, and was followed by a stabilisation of the affected economies. In contrast, the COVID-19 pandemic which began in 2020, was an exogenous shock that led to a different set of economic dynamics. Given the macroeconomic stability in the 2015-2019 period, this study isolated the effects of low interest rates and liquidity on banks' market power, providing clearer insights into how these conditions influenced bank performance.

Bank-level information was collected from the Orbis Bank Focus database of Bureau van Dijk. All monetary quantities are expressed in thousands of dollars, and only consolidated financial statements were considered. The author examined the bank history for each individual entity and considered whether any was involved in an M&A during the period of study, removing all banks with inconsistencies

[4] See: Battesse and Coelli (1992) and Greene (2005).

or missing values. Moreover, following Beck and Casu (2017), to guarantee that selected banks engage in comparable services, the analysis was narrowed to those entities with a loan-to-asset ratio higher than 10%. After applying these selection criteria, the sample available for estimation comprises a total of 1,259 observations for 272 banks, including only those classified as commercial. Regarding the sources of the contextual variables employed, market concentration information was gathered from the structural financial indicators database provided by the European Central Bank (ECB). Data on financial development were obtained from the IMF financial development index database, whilst bank capital regulation information was collected from the financial stability board (FSB) publicly available official bank lists on capital requirements. Finally, the overnight interest rate was selected as a proxy to control for the monetary policy stance since it is widely accepted as the prevailing operational target of monetary policy.[5] The data were obtained from both the European Commission Eurostat exchange and interest rates dataset and the ECB statistical data warehouse, which provides data on overnight or short-term interest rates for all EU countries.

4.2. Descriptions of variables

Regarding the bank-level variables employed in the estimation of the stochastic frontier (equation 13), following standard practice, total revenues *TR* were computed as the sum of total interest income and other operating income, whereas total costs *C* were defined as the sum of total interest expenses, staff expenses and other operating expenses (related to banks' operations other than staff and administrative expenses). Following the intermediation approach, total output *Y* was given by the sum of loans and other interest earning assets. For the input prices, the price of deposits W_d was defined as the ratio of interest expenses to total deposits, the price of capital W_k was the ratio between other operating expenses and fixed assets, and the price of labour W_l was proxied by the ratio between personnel expenses and total assets given that information on total employees was not readily available in most observations. Table 1 shows the descriptive statistics for the core variables.

Table 1. Raw variables employed in the stochastic frontier estimation. Definitions and summary statistics

Variable name	Description	Mean	Std. dev.	Min	Max
TR	Total revenue (1)	3.058	7.770	0.076	6.920
C	Total cost (1)	3.474	9.445	0.047	7.940
RC	Revenue to cost ratio (*TR*/*C*)	1.268	0.466	0.245	4.690
Y	Total output (1)	2.340	4.510	0.077	2.410
W_d	Price of the deposit ratio	0.013	0.018	0.000	0.502
W_l	Price of the labour ratio	0.011	0.013	0.000	0.308
W_k	Price of the capital ratio	9.463	0.864	0.010	17.084
E	Total equity (1)	9.437	2.200	0.037	19.800

Note: (1): million U.S. dollars. Number of observations: 1259. Number of banks: 272.

Source: BankFocus database.

Regarding the contextual variables employed in equation (14), *banking market concentration* was controlled, including the Hirschman-Herfindahl index (*HHI*) for total assets. Financial development variables were incorporated following the multidimensional approach of Čihák et al. (2012) and Svirydzenka (2016), offering nine indices to measure the levels of depth, access and efficiency with which financial institutions and financial markets performed for a sample of 183 countries. The indices are presented at three different levels of aggregation. The most disaggregated level was composed of *FID*, *FIA*, *FIE*, *FMD*, *FMA*, and *FME* indices, where the letter *I* denoted institutions and *M* markets, whilst *D*, *A*, and *E* denoted depth, access, and efficiency. Note that since the objective of this study was to analyse how the industry-specific environment affects banks' market power, only the depth (*FID*) and

5 According to Nautz and Scheithauer (2011), central banks adapted their monetary policy instruments to ensure that the overnight rate closely follows the central bank's key policy rate and that its volatility remains stable.

access (*FIA*) indices were considered as proxies for financial institution development[6]. The efficiency dimension was excluded from the analysis as it was assessed by employing banks' performance indicators, which were not direct proxies to control for the industry-specific context in each country. Moreover, following Tan (2016), development of financial markets was controlled by its level of magnitude (*FMD*). *Banks' capital regulation* was approximated by a dummy variable controlling for global systemically important banks (*G-SIBs*) equal to 1 if the bank was listed by the FSB as systemically important, and 0 otherwise in any year within the period 2011-2019. In relation to capital buffers, *Buffer* variable was computed as the difference between the ratio of equity to total assets and the minimum capital adequacy ratio (8%), whilst *monetary policy* was controlled by the overnight interest rate or, in its absence, the three-month money market interest rate (both defined as *IR*). For EMU countries, the euro over-night index average (EONIA) was the reference, whereas the reference interest rate for non-EMU members varied from country to country[7] (e.g. in the UK, the sterling OIS market considers the sterling overnight interbank average index (SONIA) reported by the Wholesale Market Brokers' Association to be its overnight rate reference). Table 2 provides a summary of the definitions and sources for these contextual variables.

Table 2. Contextual variables. Definitions and data sources

Variable name	Description	Source
HHI	Hirschman-Herfindahl index for total assets	ECB banking structural financial indicators database
FID	Financial institutions' depth Normalised and concentrated index from: – Private-sector credit to GDP – Pension fund assets to GDP – Mutual fund assets to GDP – Insurance premiums, life and nonlife, to GDP	IMF financial development index database (IMF WP/16/5)
FIA	Financial institutions' access Normalised and concentrated index from: – Bank branches per 100,000 adults – ATMs per 100,000 adults	IMF Financial Development Index Database (IMF WP/16/5)
FMD	Financial markets' depth Normalised and concentrated index from: – Stock market capitalization to GDP – Stocks traded to GDP – International debt securities of the government to GDP – Total debt securities of financial corporations to GDP – Total debt securities of nonfinancial corporations to GDP	IMF Financial Development Index Database (IMF WP/16/5)
GSIB	Dummy variable equal to 1 if the bank is listed as a global systematically important bank and 0 otherwise; in any year within the period 2011-2019.	Own elaboration. Data on G-SIBs from Financial Stability Board (FSB) official banks' lists
Buffer	Capital buffer = Equity/Total Assets – minimum capital adequacy ratio (8%)	Own elaboration. Data on equity and total assets from BankScope and BankFocus databases
IR	Overnight or short-term interest rates For EMU countries: – euro over-night index average (EONIA) For non-EMU countries: – Overnight/three-month interest rates; e.g. for the UK: sterling overnight interbank average index (SONIA)	European Commission Eurostat exchange and interest rates dataset and European Central Bank (ECB) statistical data warehouse.

Source: own elaboration.

6 Traditionally, banking literature measured the degree of financial development by looking at a proxy for financial depth or access. For instance, most studies on financial development and economic growth employed the ratio of private credit to GDP as a proxy for depth (see e.g. De Gregorio, & Guidotti, 1995; Caporale et al., 2015; and Ruiz, 2018).

7 From the EU-28, the overnight/short-term interest rate information was not readily available for Estonia, Lithuania, Slovakia, and Slovenia for most of the years of the sample period. Thus, banks in these countries were excluded from the analysed sample.

5. Empirical model and estimation results

5.1. Model specification

From the methodology described in Section 3, the model specification is as follows:

$$RC_{\ it} = \beta_0 + \beta_1 \ln(Y)_{it} + \beta_2\, ln\left(\frac{w_1}{w_3}\right)_{it} + \beta_2\, ln\left(\frac{w_2}{w_3}\right)_{it} + \beta_3\, ln(E)_{it} + u_{it} + v_{it} \tag{19}$$

$$\begin{aligned} u_{it} = \delta_0 + \delta_1\,(IR \cdot EMU)_{it} + \delta_2\,(IR \cdot NOEMU)_{it} + \delta_3 FIA_{it} + \delta_4 FID_{it} \dots \\ +\delta_5 FMD_{it} + \delta_6 (HHI \cdot EMU)_{it} + \delta_7 (HHI \cdot NOEMU)_{it} \dots \\ +\delta_8 Buffer_{it} + \delta_9 (GSIB \cdot Buffer)_{it} + \varepsilon_{it}. \end{aligned} \tag{20}$$

Equation (19) presents the stochastic frontier, where the revenue share in total cost *RC* depends on the production of loans and other interest earning assets *Y*, on the price of inputs (being the price of deposits w_1) and the price of physical capital w_2 both normalised by the price of labour w_3 to guarantee the regulatory condition of homogeneity in input prices of the translog cost function, and on the level of total equity *E*, given that loans and other interest earning assets *Y* can also be funded by employing capital (Hughes, & Mester, 1993; Mester, 1996).

Table 3. Sample statistics of the variables employed in the stochastic frontier and u estimation

Sample	EU banks (whole sample)				EMU banks				Non-EMU banks			
Frontier variables	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max
Revenue to cost ratio (***RC***)	1.268	0.466	0.245	4.690	1.117	0.336	0.245	3.071	1.491	0.536	0.297	4.690
Total output (ln ***Q***)	16.816	1.977	11.247	21.604	17.106	1.827	11.329	21.453	16.389	2.109	11.247	21.604
Price of the deposit ratio (ln $\boldsymbol{W_d}$)	0.006	1.096	-4.654	5.100	0.083	1.010	-4.654	5.100	-0.109	1.203	-3.178	4.065
Price of the capital ratio (ln $\boldsymbol{W_k}$)	5.029	1.475	-0.866	15.601	5.091	1.233	1.848	11.794	4.938	1.769	-0.866	15.601
Equity (ln ***E***)	14.550	1.771	8.225	19.103	14.800	1.643	8.225	18.672	14.182	1.887	8.714	19.103
Contextual variables												
Overnight/short-term interest rate (***IR***)	-0.002	0.556	-0.580	2.520	-0.302	0.103	-0.390	-0.020	0.411	0.652	-0.580	2.520
IR∗EMU)	-0.168	0.169	-0.390	0.000	-0.282	0.125	-0.390	0.000	0.000	0.000	0.000	0.000
(***IR∗NO EMU***)	0.166	0.461	-0.580	2.520	0.000	0.000	0.000	0.000	0.411	0.652	-0.580	2.520
Financial institution access (***FIA***)	0.723	0.192	0.163	1.000	0.761	0.198	0.163	1.000	0.668	0.167	0.299	0.935
Financial institution depth (***FID***)	0.666	0.259	0.125	1.000	0.629	0.166	0.194	0.839	0.719	0.347	0.125	1.000
Financial market depth (***FMD***)	0.633	0.296	0.042	0.949	0.669	0.258	0.042	0.949	0.580	0.338	0.045	0.945
Herfindahl-Hirschman index for total assets	0.114	0.107	0.025	0.460	0.092	0.061	0.025	0.316	0.146	0.145	0.046	0.460
HHI∗EMU	0.055	0.065	0.000	0.316	0.092	0.061	0.025	0.316	0.000	0.000	0.000	0.000
HHI∗NO EMU)	0.059	0.117	0.000	0.460	0.000	0.000	0.000	0.000	0.146	0.145	0.046	0.460
Capital buffer *Buffer* (*Equity/Total Assets*) – 8%	0.020	0.046	-0.071	0.564	0.017	0.040	-0.066	0.182	0.024	0.052	-0.071	0.564
GSIB∗Buffer	0.000	0.010	-0.047	0.096	-0.001	0.010	-0.045	0.096	0.001	0.011	-0.047	0.078
Observations	1259				750				509			

Note: EMU (= 1 if the bank belongs to an EMU country) ; NO EMU (= 1 if the bank belongs to a Non-EMU country); and G-SIB (= 1 if the bank is Global Systemically Important)

Source: own elaboration.

Equation (20) includes the set of exogenous contextual variables that might affect the mean distribution of u_{it}. Table 3 offers the sample statistics of the variables employed in equations (19) and (20). Descriptive statistics of the overnight/short-term interest rate *IR* show that on average, policy rates are higher in non-EMU countries and present significant variability compared to those in euro zone countries, reflecting the different monetary policy approaches taken by EMU and non-EMU authorities. Furthermore, given that the potential transmission mechanism of monetary policy to banks' market power is not straightforward and may differ between eurozone and non-EMU countries, two interaction terms with *IR* were introduced in the model. The first term involved multiplying *IR* by a dummy variable defined as EMU, equal to 1 if the bank belongs to an EMU country, while the second term involved multiplying *IR* by a dummy non-EMU equal to 1 if the bank belongs to a non-EMU country, which allowed to estimate the independent effects of the policy interest rate on banks' market power for each group of countries.

In relation to financial development, the available data showed that EMU institutions are more accessible for clients, and their assets represent a higher proportion of the country's GDP than those of non-EMU entities. Moreover, data on capital buffers showed that both groups of countries presented low levels of capital beyond the regulatory requirement 8%, and this proportion becomes minimal for G-SIBs in both groups of countries. An interaction term $(GSIB \cdot Buffer)$ was also included to provide information on how extra capital requirements directed to G-SIBs may affect their level of market power. As no direct causality from concentration to competition was demonstrated, and given that the effect of market concentration on banks' market power may also be conditioned by the existence of differences in idiosyncratic characteristics of the environment such as the regulatory conditions, two interaction terms for *HHI* with both EMU and non-EMU countries were included.

In relation to potential endogeneity concerns derived from the choice of the contextual variables included in equation (20), Karakaplan and Kutlu (2017) found evidence of endogeneity from *HHI* in cost function frontier models. For this reason, in the robustness analysis the effects on the estimates from this potential issue were controlled by estimating the model (19) and (20) and eliminating the variable *HHI* from equation (20).

Finally, the author estimated the traditional Lerner index as:

$$Lerner = \frac{P-Mc}{P} \ . \tag{21}$$

where the price was captured by the share of income to assets, while the marginal cost was estimated from a trans-log cost function which includes deposits, wages, and other expenses as inputs.

5.2. Estimation results

Table 4 presents the ML results for the simultaneous estimation of equations (19) and (20) following the Battese and Coelli (1995) methodology. These results suggest a negative short-term relation between the operational target of monetary policy and banks' markup for non-EMU countries, yet the results indicated that overnight short-term interest rates *IR* affected positively banks' markup in EMU countries. Many loans, especially in the consumer and business sectors, have variable interest rates tied to short-term benchmark rates, whereas in this case, as overnight rates increased, the interest income generated from these variable-rate loans also increased, positively impacting banks' markups.

Moreover, in line with Tan and Floros (2012), the estimation results suggest that more accessible financial institutions *FIAs* (proxied by the number of bank branches and ATMs per 100,000 adults) corresponded to lower markups. The results also showed that the magnitude of stock markets *FMD* (proxied by stock market capitalisation to GDP, stocks traded to GDP, among others) revealed a positive relation with the markup on interest-earning assets.

Table 4. Estimation results of the ML random-effects stochastic frontier model

Dependent variable	(1) Revenue to cost ratio (*RC*)
Frontier variables	
Ln *Q*	-0.102*** (0.021)
Ln W_d	-0.025** (0.010)
Ln W_k	-0.072*** (0.008)
Ln *E*	0.111*** (0.023)
Constant	1.416*** (0.088)
Contextual variables	
IR·EMU	25.229*** (6.472)
IR·NOEMU	-0.918*** (0.309)
FIA	-1.805*** (0.677)
FID	-2.012 (1.310)
FMD	2.557* (1.342)
HHI·EMU	1.707* (0.745)
HHI·NOEMU	-0.117* (0.680)
Buffer	6.458*** (1.739)
GSIB·Buffer	36.33* (20.67)
Log likelihood	-364.629
Wald chi	228.71
Observations	1,259

Note: This table reports the estimation results for the simultaneous estimation of stochastic frontier equations and the direct markup term u (which permits the introduction of z-explanatory variables or contextual variables). Estimates were obtained by employing the ML method for simultaneous estimation of the parameters of the frontier and u. The truncated normal specification assumptions of Battese and Coelli (1995) applied. Then employing these estimates an adjusted Lerner index was computed following equations (11) and (12). The analysis used Call Report financial data at bank level published by Orbis Bank Focus over the period 2015-2019. The working sample consisted of 1,259 observations corresponding to 272 commercial banks operating in the EU. All variables are defined in Tables 1 and 2. Heteroskedasticity-robust t-statistics are reported in parentheses below the coefficient estimates. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Source: own elaboration.

Note that a highly significant and positive effect of capital buffers on banks' markups was detected. Moreover, the sign and magnitude of the marginal effect for the interaction term $(G-SIBs \cdot Buffer)$ indicated that for global systematically important banks, an increase in their level of capital buffer was highly and significantly related to higher markups.

Table 5. Estimation results of the ML random-effects stochastic frontier model for non-EMU banks

Dependent variable	(1)	(2)
	Revenue to cost ratio (RC)	Revenue to cost ratio (*RC*)
Frontier variables		
Ln *Q*	-0.053** (0.042)	-0.052** (0.043)
Ln W_d	-0.019** (0.022)	-0.030** (0.022)
Ln W_k	-0.102*** (0.014)	-0.100*** -0.014
Ln *E*	0.085* (0.045)	0.084* (0.046)
Constant	1.216*** (0.170)	1.202*** (0.177)
Contextual variables		
IR	-1.752*** (0.572)	
IR>0		-1.435** (0.652)
FIA	-0.564* (0.712)	-0.995 (1.194)
FID	-8.473** (3.524)	-9.289** (4.511)
FMD	8.980*** (3.472)	10.645** (4.697)
HHI	-1.732 (1.501)	-3.105 (2.071)
Buffer	7.834*** (2.720)	9.167** (3.631)
GSIB·Buffer	-0.779 (13.016)	-2.377 (16.457)
Log likelihood	-278.027	-290.159
Wald chi	98.09	98.76
Observations	509	509

Note: This table reports the estimation results for the simultaneous estimation of stochastic frontier equation and the direct markup term u (which permits the introduction of *z* explanatory variables or contextual variables). Estimates were obtained by employing the ML method for simultaneous estimation of the parameters of the frontier and *u*. The truncated normal specification assumptions of Battese and Coelli (1995) applied. Then employing these estimates an adjusted Lerner index was computed following equations (11) and (12). Column (1) shows the estimation results when including all values of the short-term interest rate *IR*, and Column (2) shows the estimation results when including only positive values of *IR*. The analysis used Call Report financial data at bank level published by Orbis Bank Focus over the period 2015-2019. The working sample consisted of 509 observations corresponding to 117 commercial banks operating in non-EMU countries. All variables are defined in Tables 1 and 2. Heteroskedasticity-robust t-statistics are reported in parentheses below the coefficient estimates. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Source: own elaboration.

Table 6. Posterior mean estimates of the adjusted Lerner index and scale elasticities

Estimated Lerner index	EU	EMU	Non-EMU
Mean	**0.203**	**0.134**	**0.304**
Observations	1,259	750	509
Estimated cost elasticity (1)	EU	EMU	Non-EMU
Mean	**0.964**	**0.956**	**0.976**
Observations	1,259	750	509

Note: This table shows the mean estimates of the Lerner index and scale elasticities computed with contextual variables, employing the estimation results in column (1) in Table 4. Note (1): given that returns to scale RTS= (1/ε), then ε < 1 indicates increasing returns to scale (economies of scale), ε 1 indicates constant returns to scale and ε > 1 indicates decreasing returns to scale (diseconomies of scale).

Source: own elaboration.

Table 7. Posterior mean estimates of the traditional Lerner index

Estimated Lerner index	EU	EMU	Non-EMU
Mean	**0.250**	**0.203**	**0.319**
Observations	1,259	750	509
Estimated cost elasticity (1)	EU	EMU	Non-EMU
Mean	**0.909**	**0.897**	**0.926**
Observations	1,259	750	509

Note: This table shows the mean estimates of the traditional Lerner index estimation results. Note: (1) given that returns to scale RTS = 1/ε, then ε < 1 indicates increasing returns to scale (economies of scale), ε = 1 indicates constant returns to scale and ε> 1 indicates decreasing returns to scale (diseconomies of scale).

Source: own elaboration.

Tables 6 and 7 showed the posterior means of the Lerner index and the cost elasticities. First, regarding the cost elasticity estimates, EU banks in the sample operated at increasing returns to scale, and these results were consistent with the empirical findings on economies of scale for EU banks for the period 2000-2011 (see Beccalli et al., 2015). Second, comparing the results in Tables 6 and 7, the mean Lerner index estimates suggested that if contextual conditions were considered, the adjusted Lerner index estimates were significantly levelled down for the whole sample (EU) and for each subgroup of countries (EMU and non-EMU) in comparison to traditional Lerner index estimates. These differences could suggest that calculations of the Lerner index without controlling for these conditions, such as the monetary policy in their respective countries, may lead to biased estimations. Furthermore, the mean Lerner index estimates showed that non-EMU banks enjoy, on average, higher levels of market power. Looking at its evolution over time, Figure 1 reveals that when controlling for these conditions, the mean Lerner index estimations were levelled down for the entire period of study in the whole sample (EU) and in each subgroup (EMU and non-EMU).

In order to examine the direct impact of monetary policy on market power, Table A1 in the appendix presents the results where the short-term interest rate *IR* is considered the only contextual variable in the model. One can observe that the effect of *IR* was negative and significant in the case of Nordic and Central-Eastern countries, and not for UK banks. It is noteworthy that for Eurozone banks, the effect of IR was strong and positive, supporting the results shown in Table 4 for the full sample of banks. This result supports the view that increasing interest rates in a NIRP environment had a positive impact on banks' market power, most likely driven by a shift towards non-interest income sources.

Table 8. Mean estimates of the H-statistic index

Traditional H-statistic	EU	EMU	Non-EMU
Mean	**0.418**	**0.510**	**0.282**
Observations	1,259	750	509
Adjusted H-statistic	EU	EMU	Non-EMU
Mean	**0.394**	**0.450**	**0.270**
Observations	1,259	750	509

Note: This table presents the mean estimates of the H-statistic. The traditional H-statistic estimation followed the methodology applied by Anginer, Demirgüç-Kunt, and Zhu (2014). The adjusted H-statistic estimation followed this methodology and incorporated the z-explanatory variables of equation (12).

Source: own elaboration.

Finally, a robustness test was conducted by splitting the sample according to the banks' characteristics. Table A2 in the Appendix shows the mean estimates of the Lerner index and scale elasticities for sub-samples by bank size and default risk. The size split categorised banks as large if their total assets exceeded the 50th percentile of the distribution. The risk split categorised banks as those of higher-risk if the z-score was below the 50th percentile of the distribution. By comparing the results in Table A2 with those obtained for the full sample of banks presented in Tables 5 and 6, one can observe that in all sub-samples the market power of EU banks decreased when the contextual variables were included in the model to estimate the adjusted Lerner index. It is also noteworthy that, on average, controlling for the influence of existing differences in the contextual variables across countries, small and high-risk banks exhibited higher indices of market power.

Table 9. Post-estimation statistics of the adjusted Lerner index by country over the period 2015-2019

Country	Observations	Mean	Std. dev.	Min	Max
AUSTRIA	55	0.093	0.029	0.048	0.175
BELGIUM	27	0.095	0.048	0.039	0.231
BULGARIA	35	0.334	0.158	0.096	0.626
CROATIA	15	0.209	0.089	0.089	0.408
CYPRUS	10	0.122	0.041	0.059	0.184
CZECHIA	29	0.385	0.147	0.153	0.683
DENMARK	82	0.307	0.124	0.087	0.715
ESTONIA	15	0.523	0.072	0.399	0.635
FINLAND	19	0.182	0.088	0.096	0.336
FRANCE	282	0.119	0.060	0.039	0.472
GERMANY	50	0.126	0.108	0.056	0.589
GREECE	20	0.118	0.042	0.044	0.220
HUNGARY	30	0.231	0.091	0.114	0.403
IRELAND	15	0.108	0.029	0.049	0.167
ITALY	29	0.163	0.118	0.056	0.561
LATVIA	24	0.189	0.158	0.041	0.497
LUXEMBOURG	15	0.085	0.033	0.049	0.173
MALTA	15	0.134	0.063	0.063	0.279
NETHERLANDS	31	0.097	0.035	0.058	0.189
POLAND	55	0.183	0.056	0.094	0.309
PORTUGAL	30	0.081	0.021	0.054	0.152
ROMANIA	20	0.281	0.080	0.132	0.375
SLOVAKIA	15	0.283	0.142	0.061	0.493
SLOVENIA	20	0.238	0.102	0.073	0.415
SPAIN	78	0.117	0.073	0.043	0.505
SWEDEN	25	0.458	0.178	0.151	0.725
UNITED KINGDOM	218	0.320	0.165	0.058	0.896
Total	*1259*	*0.203*	*0.150*	*0.039*	*0.896*

Source: own elaboration.

Table 9 and Figure 2 provide the average adjusted Lerner index estimations for each country in the period of study (2015-2019). The lowest mean adjusted Lerner estimations applied to Portugal and Luxembourg (0.08), followed by Austria (0.09), whereas countries with the highest levels of banking market power were Estonia (0.52), followed by Sweden (0.46) and Czechia (0.39).

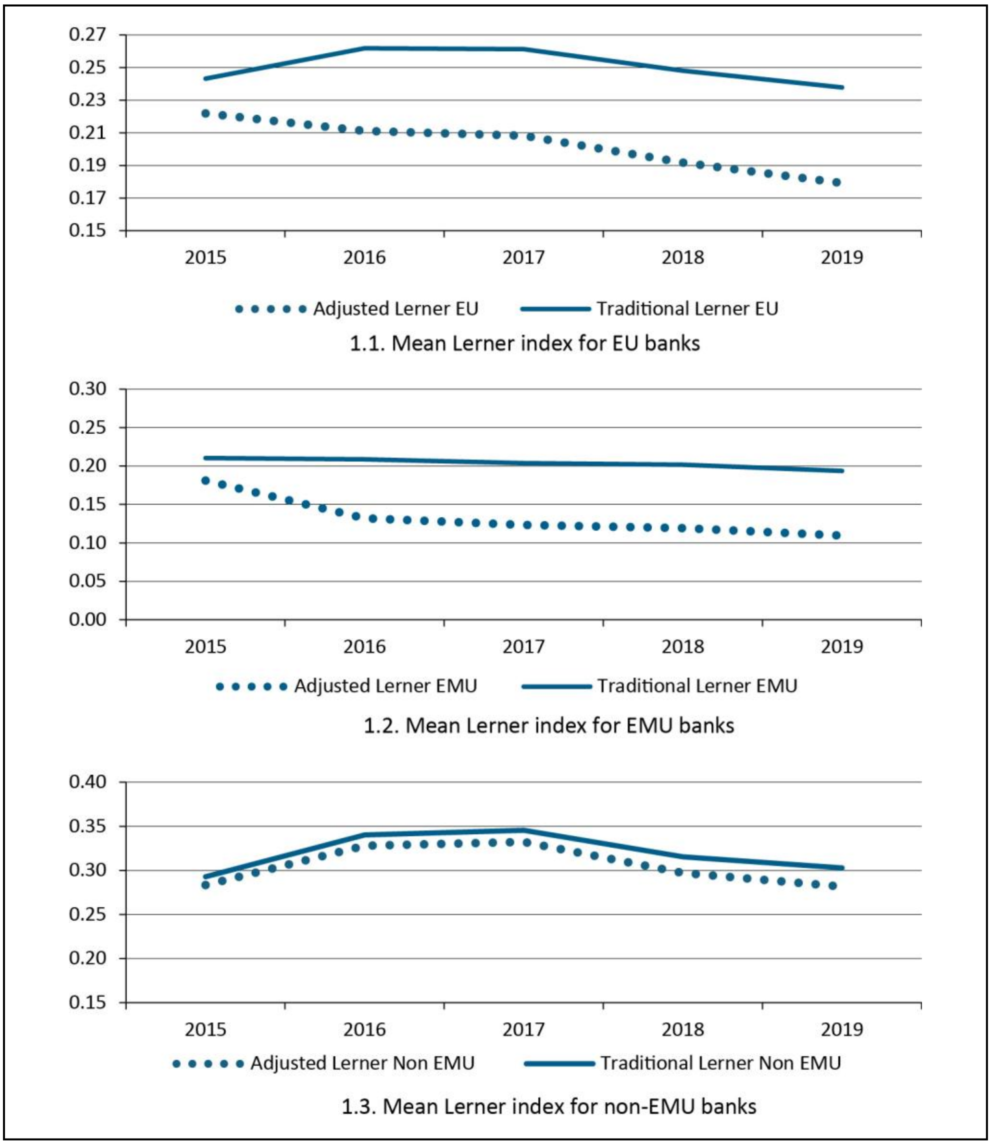

Fig. 1. Evolution of the estimated adjusted Lerner vs. traditional Lerner estimates

Source: own elaboration.

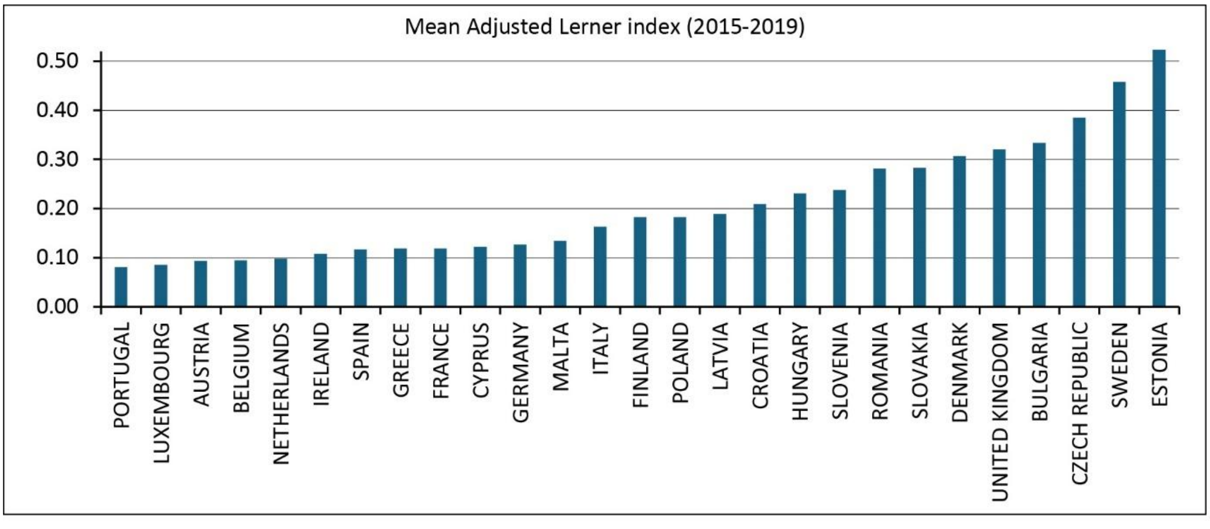

Fig. 2. Mean adjusted Lerner index by country

Source: own elaboration.

To obtain further information on the higher levels of banking market power in non-EMU countries, the author analysed the adjusted Lerner estimates for three subgroups of non-EMU countries: Central-Eastern countries (i.e. Bulgaria, Croatia, Czechia, Estonia, Hungary, Latvia, Poland, Romania, Slovakia, and Slovenia), Nordic countries (Denmark, Norway and Sweden) and the UK. Figure 3 presents the evolution of the adjusted Lerner index estimates for the three groups of non-EMU countries along with the EMU series, showing that from the non-eurozone countries, the UK and Nordic countries recorded the highest levels of banking market power. The Central-Eastern countries demonstrated lower levels of the adjusted Lerner index and appeared to align slightly more with the trends of EMU countries.

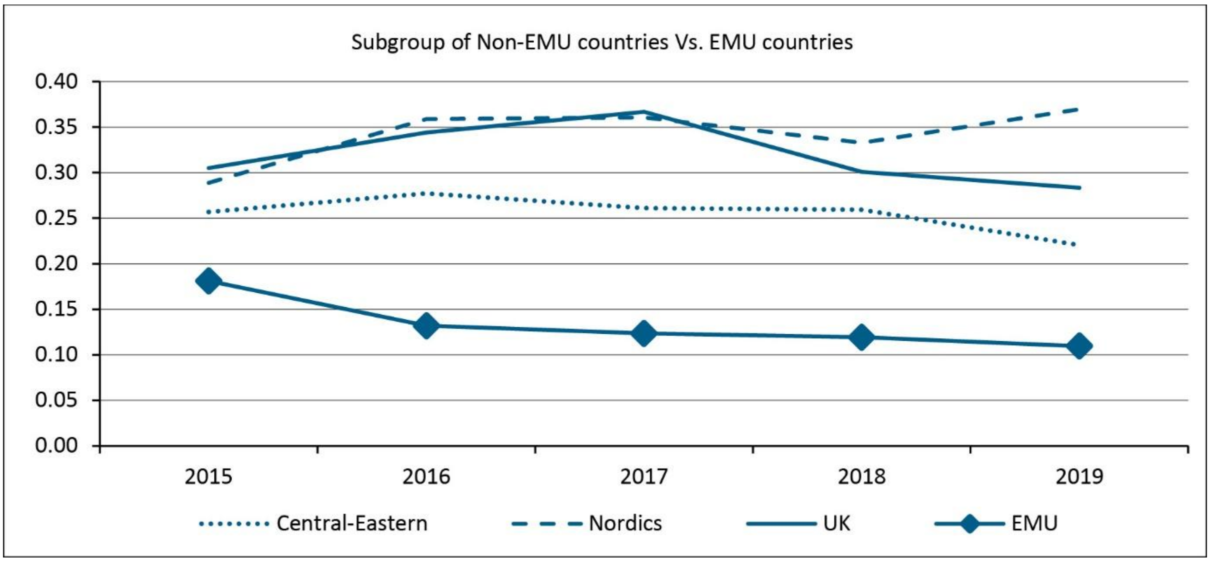

Fig. 3. Mean adjusted Lerner index by subgroup of countries

Source: own elaboration.

6. Discussion

The analysis revealed that the traditional Lerner index overestimated banks' market power in EMU countries, largely because of the effects of the NIRP implemented by the ECB during the period 2015--2019. These findings are in sharp contrast with those obtained on average for the non-EMU banking system, where the differences between the traditional and adjusted Lerner index were small, indicating that, in this case, the effect of contextual variables on market power was weak.

These results are supported by research findings obtained by Igan et al. (2021), showing that, once the decline in rates was accounted for, the Lerner index for advanced economies did not demonstrate any significant upward trend during the period 2000-2016, whilst Altunbas et al. (2023) showed that the NIRP led to an increase in the market power of euro-area banks.

Moreover, research findings suggest that small banks exercise higher market power, in line with the literature suggesting that small banks, which often rely on relationship lending (Degryse, & Van Cayseele, 2000), can leverage their informational advantage over customers and the limited credit options available to borrowers to enhance their market power. Additionally, estimation results showed that banks with higher default risk exercise more market power. This is in line with the strand of the literature that supports the existence of mechanisms leading to a 'competition-stability' outcome. Boyd and De Nicoló (2005) pointed out that market power enhances bank portfolio risks, and found that banks with market power tend to raise loan rates and so borrowers, confronted with higher interest costs, optimally adjust their investment policies in favour of higher risk. In accordance with this view, Martínez-Miera and Repullo (2010) argued that competition in the loan market may erode bank stability by diminishing banks' margins.

Furthermore, research findings suggested that the policy response to the GFC in the euro area did not seem to have resulted in a fundamental increase in market power. Even though the Central Bank of Sweden brought its main intervention rate into negative territory from 2015 to 2019 when the repo rate was gradually brought back to zero, the adjusted Lerner index remained high and stable through this period mainly because Swedish banks could operate at low-cost-to-income ratios relative to their EU peers (Carletti et al., 2020). In the case of the Bank of England, this central bank set its official rate to 0.25% in August 2016, mainly in response to the economic uncertainty following the Brexit referendum. In this context, Figure 3 shows a change in the UK trend of the mean Lerner index since 2017, and this decrease in market power might be related with the post-referendum increase in economic uncertainty in the UK. Further research is required to shed light on these two banking systems.

It is also worth noting that variations in the level of bank market power across countries may lead to asymmetrical effects of the single monetary policy, given that market power reduces its effectiveness (Leroy, 2014). In light of the results discussed in this article, this could be an important issue in the context of the EMU banking system, regarding the wide differences in the structural component of market power across the countries shown in Figure 2.

7. Conclusions

This paper aimed to provide market power estimations for EU banks for the period 2015-2019, while controlling for the influence of conditions that are known to affect bank performance. Igan et al. (2021) demonstrated that the traditional Lerner index becomes less informative as an indicator of market power in the context of near-zero or negative interest rates. Therefore, controlling for the influence of monetary policy is crucial when making cross-country comparisons of banking market power in the EU. To achieve this, the author provided an alternative estimation of the Lerner index, based on the stochastic frontier model of market power by Kumbhakar et al. (2012), incorporating the effect of contextual variables. These contextual conditions, such as monetary policy, capital regulation, the degree of financial system development, and market structure, set the playing field for proper cross-country comparisons.

The estimation results revealed that when market conditions were included, the estimated Lerner index for the entire sample of EU banks was levelled down compared to traditional Lerner index estimates. This supports the view that in the context of near-zero policy rates following the global financial crisis, the traditional Lerner index may have overestimated the market power of banks. Furthermore, the results reflected a notable divergence in market power levels between EMU and non-EMU banks over the study period. Specifically, the UK and the Nordic countries demonstrated the highest levels of banking market power, while the Central-Eastern countries displayed lower adjusted Lerner indices, aligning more closely with the EMU countries.

The estimation results suggest that the traditional Lerner index tended to overestimate market power in the EMU countries under the NIRP scenario between 2015 and 2019. This was in contrast with the findings for the non-EMU banking systems, where the differences between traditional and adjusted Lerner indices were smaller, suggesting weaker effects of the contextual variables on market power in these countries.

Moreover, the results of this study support the literature suggesting that smaller banks may leverage their informational advantage over customers and the limited credit alternatives available to borrowers to increase their market power. Additionally, the findings showed that banks with higher default risk tended to exercise more market power, consistent with the competition-stability literature.

Finally, differences in market power levels across the EU countries could lead to asymmetric effects from the single monetary policy, as greater market power can reduce the policy's effectiveness (Leroy, 2014). Given the substantial differences in market power levels observed within the EU banking system, this is an important issue for future research. As the euro area continues to integrate its banking sector, understanding the implications of these differences on the broader monetary policy framework will be crucial for shaping effective and efficient policy interventions.

Further research is needed to explore the specific mechanisms by which NIRP affect market power, particularly examining how non-interest income responds to changes in policy rates. A key focus could be investigating whether banks increase market power through higher fees or other non-interest income channels in response to low or negative interest rates. As the integration of the euro area banking system progresses, future research should examine how these advancements in banking integration may affect market power dynamics, especially in relation to banks of different sizes and their ability to adapt to the changing regulatory environment.

References

Acharya, V. V., Borchert, L., Jager, M., & Steffen, S. (2021). Kicking the can down the road: Government interventions in the European banking sector. *The Review of Financial Studies*, *34*(9), 4090-4131. https://doi.org/10.1093/rfs/hhab002

Alessandri, P., & Nelson, B. (2012). Simple banking: Profitability and the yield curve. Bank of England. *Working Paper, 452*. https://doi.org/10.1111/jmcb.12172

Altavilla, C., Begenau, J., Burlon, L., & Hünnekes, F. (2024). Determinants of bank performance: Evidence from replicating portfolios. *ECB Working Paper*, *2937*. https://doi.org/10.2866/388405

Altunbas, Y., Avignone, G., Kok, Ch., & Pancaro, C. (2023). Euro area banks' market power, lending channel and stability: The effects of negative policy rates. *ECB, Working Paper*, *2790*. http://dx.doi.org/10.2139/ssrn.4368836

Angelini, P., & Cetorelli, N. (2003). Bank competition and regulatory reform: The case of the Italian banking industry. *Journal of Money, Credit, and Banking*, *35*, 663-684.

Anginer, D., Demirguc-Kunt, A., & Zhu, M. (2014). How does competition affect bank systemic risk? *Journal of Financial Intermediation*, *23*, 1-26. https://doi.org/10.1016/j.jfi.2013.11.001

Bain, J. S. (1951). Relation of profit rate to industrial concentration: American manufacturing, 1936-40. *Quarterly Journal of Economics*, *65*, 293-324. https://doi.org/10.2307/1882217

Bassett, W., Demiralp, S., & Lloyd, N. (2020). Government support of banks and bank lending. *Journal of Banking & Finance*, *112*, 105-177. https://doi.org/10.1016/j.jbankfin.2017.07.010

Battese, G. E., & Coelli, T. J. (1992). Frontier production functions, technical efficiency and panel data: with application to paddy farmers in India. *Journal of productivity analysis, 3(1)*, 153-169. https://doi.org/10.1007/BF00158774

Battese, G. E., & Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics*, *20*, 325-332. https://doi.org/10.1007/BF01205442

Baumol, W. (1982). Contestable markets: An uprising in the theory of industry structure. *The American Economic Review*, *72*(1), 1-15.

Beccalli, E., Anolli, M., & Borello, G. (2015). Are European banks too big? Evidence on economies of scale. *Journal of Banking & Finance*, *58*, 232-246. https://doi.org/10.1016/j.jbankfin.2015.04.014

Beck, T., & Casu, B. (2017). European Banking: An Overview. *The Palgrave Handbook of European Banking*, 3-24. Palgrave Macmillan. https://doi.org/10.1057/978-1-137-52144-6_1

Belotti, F., Daidone, S., Ilardi, G., & Atella, V. (2013). Stochastic frontier analysis using Stata. *The Stata Journal, 13(4)*, 719-758. https://doi.org/10.1177/1536867X1301300404

Berger, A. N., Demirgüç-Kunt, A., Levine, R., & Haubrich, J. G. (2004). Bank concentration and competition: An evolution in the making. *Journal of Money, Credit and Banking*, *36*, 434-451. https://www.jstor.org/stable/3838945

Berger, A. N., Klapper, L. F., & Turk-Ariss, R. (2009). Bank competition and financial stability. *Journal of Financial Services Research*, *35*, 99-118. https://doi.org/10.1007/s10693-008-0050-7

Berger, A. N., Kravitz, T. A., & Shibut, L. (2022). *The many facets of bank competition: Evidence from an extraordinary dataset*. Available at: https://ssrn.com/abstract=4030784 or http://dx.doi.org/10.2139/ssrn.4030784

Bikker, J. A., & Spierdijk, L. (2009). *Measuring and explaining competition in the financial sector*. Discussion Paper Series. Tjalling C. Koopmans Research Institute, Vol. 9.

Bolt, W., De Haan, L., Hoeberichts, M., Van Oordt, M. R. C., & Swank, J. (2012). Bank profitability during recessions. *Journal of Banking & Finance*, *36*, 2552-64. https://doi.org/10.1016/j.jbankfin.2012.05.011

Bolt, W., & Humphrey, D. (2015). Assessing bank competition for consumer loans. *Journal of Banking & Finance*, *61*, 127-141. https://doi.org/10.1016/j.jbankfin.2015.09.004

Boone, J. (2008). A new way to measure competition. *The Economic Journal*, *118.531*, 1245-1261. https://doi.org/10.1111/j.1468-0297.2008.02168.x

Borio, C., Gambacorta, L., & Hofmann, B. (2017). The influence of monetary policy on bank profitability. *International Finance*, *20*, 48-63. https://doi.org/10.1111/infi.12104

Bos, J. W. B., & Kool, C. J. M. (2006). Bank efficiency: The role of bank strategy and local market conditions. *Journal of Banking & Finance*, *30*, 1953-1974. https://doi.org/10.1016/j.jbankfin.2005.07.008

Boyd, J. H., & De Nicoló, G. (2005). The theory of bank risk taking and competition revisited. *The Journal of Finance*, *60*(3), 1329-1343. https://doi.org/10.1111/j.1540-6261.2005.00763.x

Bresnahan, T. F. (1989). Empirical studies of industries with market power. *Handbook of industrial organization*, *2*, 1011-1057. https://doi.org/10.1016/S1573-448X(89)02005-4

Busch, R., & Memmel, C. (2015). Banks' net interest margin and the level of interest rates. *Bundesbank Discussion Paper*, *16/2015*. https://doi.org/10.3790/ccm.50.3.363

Caporale, G. M., Rault, C., Sova, A. D., & Sova, R. (2015). Financial development and economic growth: Evidence from 10 new European Union members. *International Journal of Finance & Economics, 20*(1), 48-60. https://doi.org/10.1002/ijfe.1498

Carletti, E., Claessens, S., Fatás, A., & Vives, X. (2020). *Post-Covid-19 World*. Centre for Economic Policy Research.

Carvallo, O. V., & Ortiz, A. B. (2018). Bank capital buffers around the world: Cyclical patterns and the effect of market power. *Journal of Financial Stability*, *38*, 119-131. https://doi.org/10.1016/j.jfs.2018.02.004

Casu, B., & Molyneux, P. (2010). A comparative study of efficiency in European banking. *Applied Economics*, *35*, 1865-1876. https://doi.org/10.1080/0003684032000158109

Chaffai, M., & Coccorese, P. (2023). Banking market power and its determinants: New insights from MENA countries. *Emerging Markets Review*, *55*. https://doi.org/10.1016/j.ememar.2023.101004

Čihák, M., Demirgüç-Kunt, A., Feyen, E., & Levine, R. (2012). Benchmarking financial development around the world. *World Bank Policy Research Working Paper, 6175*. https://ssrn.com/abstract=2152254

Claessens, S., Coleman, N., & Donnelly, M. (2018). "Low-for-long" interest rates and banks' interest margins and profitability: Cross-country evidence. *Journal of Financial Intermediation*, *35*(A), 1-16. https://doi.org/10.1016/j.jfi.2017.05.004

Cruz-García, P., Fernandez de Guevara, J., & Maudos, J. (2017). The evolution of market power in European banking. *Finance Research Letters*, *23*, 257-262. https://doi.org/10.1016/j.frl.2017.06.012

De Gregorio, J., & Guidotti, P. E. (1995). Financial development and economic growth. *World development, 23*(3), 433-448. https://doi.org/10.1016/0305-750X(94)00132-I

Degryse, H., & Van Cayseele, P. (2000). Relationship lending within a bank-based system: evidence from European small business data. *Journal of Financial Intermediation*, *9*(1), 90-109. https://doi.org/10.1006/jfin.1999.0278

De Jonghe, O., Diepstraten, M., & Schepens, G. (2016). Competition in EU banking. *The Palgrave Handbook of European Banking*, 187-211. https://doi.org/10.1057/978-1-137-52144-6_8

Delis, M., & Tsionas, E. G. (2009). The joint estimation of bank-level market power and efficiency. *Journal of Banking & Finance*, *33*, 1842-1850. https://doi.org/10.1016/j.jbankfin.2009.04.006

European Central Bank (ECB). (2018). *Financial integration in Europe*.

Fare, R., Grosskopf, S., & Margaritis, D. (2024). *Market Power, Economic Efficiency and the Lerner Index.* World Scientific Publishing Company.

Fonseca, R., & González, F. (2010). How bank capital buffers vary across countries: The influence of cost of deposits, market power and bank regulation. *Journal of Banking & Finance*, *34*, 892-902. https://doi.org/10.1016/j.jbankfin.2009.09.020

Gambacorta, L., & Iannotti, S. (2007). Are there asymmetries in the response of bank interest rates to monetary shocks? *Applied Economics*, *39*(19), 2503-2517. https://doi.org/10.1080/00036840600707241

Goyal, R., Brooks, P. K., Pradhan, M., Tressel, T., Dell'Ariccia, G., Leckow, R., & Pazarbasioglu, C. (2013). *A banking union for the euro area*. Chapter 9. IMF Staff Discussion Note 13/01, 2013.

Greene, W. (2005). Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. *Journal of Econometrics, 126*(2), 269-303. https://doi.org/10.1016/j.jeconom.2004.05.003

Hakenes, H., & Schnabel, I. (2011). Capital regulation, bank competition, and financial stability. *Economics Letters*, *113*, 256-258. https://doi.org/10.1016/j.econlet.2011.07.008

Hannan, T. H. (1991). Foundations of the structure-conduct-performance paradigm in banking. *Journal of Money, Credit and Banking*, *23*(1), 68-84. https://doi.org/10.2307/1992764

Hannan, T. H., & Berger, A. N. (1997). The rigidity of prices: Evidence from the banking industry. *Journal of Reprints for Antitrust Law and Economics*, *27*, 245.

Hughes, J. P., & Mester, L. J. (1993). A quality and risk-adjusted cost function for banks: Evidence on the "too-big-to-fail" doctrine. *Journal of Productivity Analysis*, *4*, 293-315. https://doi.org/10.1007/BF01073414

Igan, D., Martinez Peria, M. S., Pierri, N., & Presbitero, A. (2021). When they go low, we go high? Measuring bank market power in a low-for-long environment. *IMF Working Paper*, https://ssrn.com/abstract=4026327

Kalirajan, K. (1981). An econometric analysis of yield variability in paddy production. *Canadian Journal of Agricultural Economics*, *29*, 283-294. https://doi.org/10.1111/j.1744-7976.1981.tb02083.x

Karakaplan, M. U., & Kutlu, L. (2017). Endogeneity in panel stochastic frontier models: an application to the Japanese cotton spinning industry. *Applied Economics, 49(59)*, 5935-5939. https://doi.org/10.1080/00036846.2017.1363861

Kumbhakar, S. C., Ghosh, S., & McGuckin, J. T. (1991). A generalized production frontier approach for estimating determinants of inefficiency in US dairy farms. *Journal of Business & Economic Statistics*, *9*(3), 279-286. https://doi.org/10.1080/07350015.1991.10509853

Kumbhakar, S. C., Baardsen, S., & Lien, G. (2012). A new method for estimating market power with an application to Norwegian sawmilling. *Review of Industrial Organization*, *40*, 109-129. https://doi.org/10.1007/s11151-012-9339-7

Kumbhakar, S. C., & Lovell, C. K. (2000). *Stochastic frontier analysis*. Cambridge university press. https://doi.org/10.1017/CBO9781139174411

Kumbhakar, S. C., & Tsionas, E. G. (2008). Scale and efficiency measurement using a semiparametric stochastic frontier model: Evidence from the US commercial banks. *Empirical Economics, 34*(3), 585-602. https://doi.org/10.1007/s00181-007-0137-2

Lee, C., & Hsieh, M. (2013). The impact of bank capital on profitability and risk in Asian banking. *Journal of International Money and Financ, 32*, 251-281. https://doi.org/10.1016/j.jimonfin.2012.04.013

Leroy, A. (2014). Competition and the bank lending channel in the eurozone. *Journal of International Financial Markets, Institutions and Money*, *31*, 296-314. https://doi.org/10.1016/j.intfin.2014.04.003

Levine, R. (2005). *Finance and Growth: Theory and Evidence*. *Handbook of Economic Growth*. Vol. 1, Chapter 12, 865-934. North-Holland. https://doi.org/10.1016/S1574-0684(05)01012-9

Love, I., & Martínez Pería, M. S. (2015). How bank competition affects firms' access to finance. *The World Bank Economic Review*, *29*(3), 413-448. https://doi.org/10.1093/wber/lhu003

Martinez-Miera, D., & Repullo, R. (2010). Does competition reduce the risk of bank failure? *The Review of Financial Studies*, *23*(10), 3638-3664. https://doi.org/10.1093/rfs/hhq057

Mason, E. S. (1939). Price and production policies of large-scale enterprises. *American Economic Review*, *29*, 61-74. https://www.jstor.org/stable/1806955

Maudos, J., & Vives, X. (2019). Competition policy in banking in the European Union. *Review of industrial organization*, *55*, 27-46. https://doi.org/10.1007/s11151-019-09687-5

Mester, L. J. (1996). A study of bank efficiency taking into account risk-preferences. *Journal of Banking and Finance*, *20*, 1025-45. https://doi.org/10.1016/0378-4266(95)00047-X

Nautz, D., & Scheithauer, J. (2011). Monetary policy implementation and overnight rate persistence. *Journal of International Money and Finance, 30*(7), 1375-1386. https://doi.org/10.1016/j.jimonfin.2011.07.005

Ortega, C. (2021). *Market power in the EU banking sector in a time of unconventional monetary policy.* Unpublished manuscript. Universidad de Málaga Institutional Repository (RIUMA). https://riuma.uma.es/xmlui/handle/10630/23147

Pitt, M. M., & Lee, L.-F. (1981). The measurement and sources of technical inefficiency in the Indonesian weaving industry. *Journal of Development Economics*, *9*, 43-64. https://doi.org/10.1016/0304-3878(81)90004-3

Ruiz, J. L. (2018). Financial development, institutional investors, and economic growth. *International Review of Economics & Finance, 54*, 218-224. https://doi.org/10.1016/j.iref.2017.08.009

Svirydzenka, K. (2016). Introducing a new broad-based index of financial development. *IMF Working Paper*, 16/5. International Monetary Fund (January). https://doi.org/10.5089/9781513583709.001

Tan, Y. (2016). The impacts of risk and competition on bank profitability in China. *Journal of International Financial Markets, Institutions and Money*, *40*, 85-110. https://doi.org/10.1016/j.intfin.2015.09.003

Tan, Y., & Floros, C. (2012). Bank profitability and GDP growth in China: A note. *Journal of Chinese Economic and Business Studies*, *10*, 267-273. https://doi.org/10.1080/14765284.2012.703541

Toolsema, L. A. (2004). Monetary policy and market power in banking. *Journal of Economics*, *83*, 71-83. https://doi.org/10.1007/s00712-003-0063-5

Tsionas, E. G., Malikov, E., & Kumbhakar, S. C. (2018). An internally consistent approach to the estimation of market power and cost efficiency with an application to U.S. banking. *Journal of Operational Research, 270*, 747-760. https://doi.org/10.1016/j.ejor.2018.04.012

Vesala, J. (1995). *Testing for competition in banking: behavioural evidence from Finland*. Bank of Finland. http://hdl.handle.net/10419/212934

Wang, H.-J., & Schmidt, P. (2002). One-step and two-step estimation of the effects of exogenous variables on technical efficiency levels. *Journal of Productivity Analysis*, *18*, 129-144. https://doi.org/10.1023/A:1016565719882

Wang, X., Han, L., & Huang, X. (2020). Bank market power and SME finance: Firm-bank evidence from European countries. *Journal of International Financial Markets, Institutions and Money*, *64*, 101162. https://doi.org/10.1016/j.intfin.2019.101162

Received: December 2023, revised: December 2024

Acknowledgements: *The author is grateful for the valuable comments and suggestions received during the presentation of this paper at the Day-Ahead Workshop on Financial Regulation held at the University of Zurich on October 13-14, 2021. This work, as an unpublished text, is presented on the following website*: https://riuma.uma.es/xmlui/handle/10630/23147.

Appendix

Table A1. Estimation results of the ML random-effects stochastic frontier model

Dependent variable	EU	EMU	EAS	NOR	UK
	(1)	(2)	(3)	(4)	(5)
	Revenue to cost ratio (RC)	Revenue to cost ratio (RC)	Revenue to cost ratio (RC)	Revenue to cost ratio (RC)	Revenue to cost ratio (RC)
Frontier variables					
Ln *Q*	-0.150*** (0.024)	-0.132*** (0.024)	-0.220*** (0.076)	-1.344*** (0.306)	-0.001** (0.065)
Ln W_d	-0.026** (0.011)	-0.028*** (0.010)	-0.079** (0.034)	0.113** (0.047)	0.135*** (0.036)
Ln W_k	-0.065*** (0.008)	-0.058*** (0.009)	-0.047** (0.023)	0.000 (0.028)	-0.133*** (0.021)
Ln *E*	0.154*** (0.025)	0.133*** (0.025)	0.292*** (0.073)	1.512*** (0.362)	-0.007 (0.071)
Constant	1.408*** (0.098)	1.498*** (0.102)	0.716*** (0.275)	1.667*** (0.417)	1.845*** (0.253)
Contextual variables					
IR	0.263*** (0.048)	2.258*** (0.000)	-0.568*** (0.171)	-1.566*** (0.348)	-154.511 (162.754)
Log likelihood	-537.536	-15.516	-60.589	-46.836	-147.505
Wald chi	230.27	186.95	59.11	39.67	55.42
Observations	1209	700	208	107	218

Note: This table reports the estimation results for the simultaneous estimation of stochastic frontier equations and the direct markup term u (which permits the introduction of *z* explanatory variables or contextual variables). Estimates were obtained by employing the ML method for simultaneous estimation of the parameters of the frontier and u. The truncated normal specification assumptions of Battese and Coelli (1995) applied. Then employing these estimates an adjusted Lerner index was computed following equations (11) and (12). These estimations only employed *IR* as contextual variable to analyse the direct impact of monetary policy on the estimation results. The analysis used Call Report financial data at bank level published by Orbis Bank Focus over the period 2015-2019. All variables were defined in Tables 1 and 2. Heteroskedasticity-robust standard errors are reported in parentheses below the coefficient estimates. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Source: own elaboration.

Table A2. Split sample analysis by bank traits

Adjusted Lerner index (model including all contextual variables)	Large	Small	High risk	Low risk
Mean	**0.193**	**0.245**	**0.290**	**0.219**
Observations	631	628	314	600
Estimated cost elasticity (1)				
Mean	**0.900**	**0.979**	**0.895**	**0.961**
Observations	631	628	314	600
Traditional Lerner index	Large	Small	High risk	Low risk
Mean	**0.235**	**0.261**	**0.300**	**0.225**
Observations	631	628	314	600
Estimated cost elasticity (1)				
Mean	**0.854**	**0.969**	**0.897**	**0.986**
Observations	631	628	314	600

Note: This table reports the mean estimates of the Lerner index and scale elasticities for samples split by bank size and default risk. The size split categorised banks as large if their total assets exceeded the 50th percentile of the distribution. The risk split categorised banks as higher-risk if their z-score was below the 50th percentile of the distribution. Note (1): given that returns to scale RTS = (1/ε), then ε < 1 indicates increasing returns to scale (economies of scale), ε = 1 indicates constant returns to scale and ε > 1 indicates decreasing returns to scale (diseconomies of scale).

Source: own elaboration.