Estimating Market Power in the EU banking system: A Stochastic Frontier Approach with Contextual Variables

Abstract

This paper aims to measure market power in the EU banking system, controlling for the influence that environmental conditions, such as monetary policy or bank capital regulation, may have on banks' performance. An empirical analysis is carried out using stochastic frontier methods and an unbalanced panel of 756 EU commercial, cooperative, and savings banks for the period 2005–2019. The estimation results reveal that including contextual variables leveled down the mean Lerner index estimates for the whole sample of banks. Furthermore, the research findings show the existence of systematic differences between EMU and non-EMU banks, with significantly higher market power levels for non-EMU banks as a group. These results also suggest growing disparities in market power among EMU banks since 2014, which may be explained by the existence of persistent barriers to integration within the EU banking market.

JEL classification: L11; D22; G21; G28

Keywords: Market power, Stochastic frontier, Bank capital regulation, Monetary policy, 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 toward 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, which was prompted by the financial deregulation process and technological advances since the 1980s. Looking at the banking integration path, clear progress was achieved from 1995 until the outbreak of the global financial crisis in 2007. From 2008 until 2012, the integration process reversed, experiencing significant divergences in interest rates among EU banks (ECB, 2018). However, since 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], a gradual recovery of banking integration has been witnessed, although it has not yet achieved precrisis levels. 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 evidences the lack of cross-border mergers within euro area banks and shows that European banking markets remain nationally based (Maudos and Vives, 2019).

The main goal of a fully integrated financial sector is to permit the transaction of financial instruments and the provision of financial services under the same conditions for all EU members. In fact, advances in EBU would lead to lower compliance, resolution and restructuring costs, the elimination of any barriers to cross-border banking activity

[1] Three features characterize 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 harmonized procedures that permit equal treatment of financial services' users (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 deposit insurance harmonized regulation.

and eventually lower bank funding costs (IMF, 2015). Therefore, advances in EU financial integration until the outbreak of the Global Financial Crisis (GFC) should be expected to have incentivized competition among EU countries.

However, since the introduction of the Euro in 1999, De Jonghe et al. (2016) show a general trend of competition deterioration in the EU. Moreover, Delis and Tsionas (2009) find significant variability between EU countries in banking market power, which may support the existence of barriers to integration.

These findings may reflect flaws of the financial integration policy steps taken and may reveal persistent fragmentation in the EU banking market. According to the ECB (2017), ligation costs, as well as divergences in legal and regulatory frameworks, constitute elements of the regulatory environment that may explain persistent barriers to integration and lead to different competition scenarios within the EU. Subsequently, to precisely assess the EU banking competition scenario, how potential 'environmental' differences among EU members could affect the ability of banks to exercise market power seems important to consider. This study aims to respond to the following research questions: Do different contextual conditions (economic policy, bank capital regulation, market structure, etc.) among EU countries affect the market power estimates of EU banks? In addition, controlling for these environmental banking differences, have EU countries converge in market power levels from 2005 to 2019? To answer these research questions, this paper provides a market power estimation for EU banks for the period 2005–2019 by controlling for the influence of environmental conditions with a known influence on banks' performance.

Extensive research has been carried out on the influence of environmental conditions on the operational efficiency of banks (Dietsch and Lozano-Vivas (2000); Bos and Kool (2006); Delis and Tsionas (2009); and Casu and Molyneux (2010)). This literature has highlighted the importance of examining the economic and regulatory environment when conducting cross-country comparative analyses of banks' efficiency. In this sense, performance comparisons of banks belonging to different markets without capturing the potential effect of divergences in their environmental conditions may lead to biased estimations and inaccurate cross-country comparisons. For instance, without controlling for regulatory, institutional, or industry-specific conditions, differences in banking market power estimates among EU countries may hide only the potential effect of divergences in their environmental conditions.

The empirical literature on the EU banking market has limited consideration of the environment when estimating banks' market power. Thus, this paper attempts to fill this gap by obtaining an environmentally controlled Lerner index estimation for proper cross-country comparisons. Detecting potential persistent divergences in market power levels among EU countries that could be explained by internal bank activity-driven barriers to integration would also be helpful.

Regarding the environmental variables employed, this study includes conditions of the banking environment that likely affect banks' market power and extend beyond the firms' decision scope. Since higher market power can be derived from higher bank profitability and because greater profits achieved by banks may signal lower banking competition (Tan, 2016), including industry-specific factors known to affect banks' profitability seems reasonable. In this respect, following Tan and Floros (2012a) and Tan (2016), the analysis includes two industry factors that affect banks' profitability: (i) market structure given that the structure-conduct-performance hypothesis (SCP) argues that higher concentration levels may translate into higher market power levels; and (ii) the development of the financial system given that more developed banking sectors are positively related to higher bank profitability (Tan and Floros, 2012b). Furthermore, this paper includes (iii) capital regulation as an additional environmental condition since the banking literature recognizes that it constitutes an industry-specific factor related to banks' profitability (Lee and Hsieh (2013); Tran et al. (2016)) and banking competition (Hackenes and Schnabel, 2011). Moreover, the effect of monetary policy (iv) is also incorporated given that short-term market interest rates have a systematic effect on banks' margins. Finally, to control for the potential effect of episodes of financial distress on bank market power derived from restructuring processes (Cubillas and Suárez (2013, 2018)), an environmental variable is included to account for the effects of both the Global Financial Crisis (GFC) of 2008 and the European debt crisis initiated in 2011.

To address such an analysis, an empirical framework is constructed based on the existing theoretical stochastic frontier model of market power developed by Kumbhakar et al. (2012), which provides the clear advantage of allowing the inclusion of exogenous contextual variables by following the specification of Battese and Coelli (1995). To the best of our knowledge, this is the first empirical paper to merge both procedures to estimate an environmentally controlled Lerner index for the EU banking market.

The paper is organized as follows. Section 2 surveys the literature on the effect of the environment on banking competition, providing a more detailed analysis of the literature regarding relationships between relevant environmental variables and banks' market power. The model and the econometric methodology employed are presented in Section 3. Then, Section 4 reports the data employed. Section 5 presents the empirical model specification and the estimation results. Finally, Section 6 summarizes the main conclusions.

2. Theoretical background

Literature focusing on analyzing the potential effect of the environment on banking competition is scarce. Recently, Tsionas et al. (2018) developed an econometric methodology to jointly estimate the efficiency and market power for a sample of US commercial banks. They are the first to introduce the effect of internal bank characteristics and some contextual variables (market concentration, the number of M&As, or the unemployment rate to control for the macroeconomic context) on market power estimates. Nonetheless, extensive research has been carried out on the influence of environmental conditions on the operational efficiency of banks (Dietsch and Lozano-Vivas (2000); Bos and Kool (2006); Delis and Tsionas (2009); and Casu and Molyneux (2010)). This literature has highlighted the importance of examining the environment when developing banks' performance cross-country comparative analyses. In this sense, performance comparisons of banks belonging to different markets without capturing the potential effect of divergences in their environmental conditions may lead to biased comparisons. For instance, without controlling for the regulatory, institutional, or industry-specific environment, differences in banking performance between countries may hide these specific environmental divergences instead of reflecting internal bank activity-driven differences.

Thus, controlling for industry-specific factors that may determine permanent differences in the average levels of banking market power between countries to some extent is important (Tan and Floros, 2012). The industry-specific determinants that might be considered are the banking market structure, bank capital regulation, and the development of the financial system. In addition, given the heterogeneity in economic policy between EMU and non-EMU countries, controlling for the effect of monetary policy on bank markup is important. Finally, due to the direct implications of economic and financial crises in the banking sector, a contextual variable might be considered to control for the effects of the global and Euro debt crises.

First, regarding the banking market structure, the structure-conduct-performance (SCP) paradigm proposes that market concentration conditions banks' competitive conduct (Mason, 1939; Bain, 1951)). However, a clear direction of causality from structure to conduct has not yet been proven (Vesala, 1995). In fact, a considerable number of authors in this field have identified structure measures as inadequate proxies for competition (Berger, 2004, 2009; Bikker and Spierdijk, 2009; Bolt and Humphrey, 2015). In this regard, Boone (2008) argues 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. Furthermore, more concentrated banking markets and intense competition may not be incompatible under certain circumstances. Baumol's Theory of Contestable Markets (Baumol, 1982) points out 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 to better assess the

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

environment in which EU banks operate is meaningful. For this reason, this study includes the Herfindahl index of total assets as an indicator of market structure. Given the lack of proven causality from structure to conduct, no prior expectation applies to the effect of this variable on the markup estimation. However, this index seems to be a useful indicator to control for a potential divergence in how market structure may affect banks' market power between EMU and non-EMU groups of banks.

A second industry-specific determinant of banks' performance is the development of the financial system. Most literature on financial development has assessed it by considering a proxy for financial depth or access. However, the term financial development implies broader significance. Levine (2005) reports that developed financial institutions efficiently allocate capital, pool savings, and screen borrowers, sufficiently monitor investments, and properly diversify risks. Moreover, according to Čihák et al. (2012, p. 4), "at the most basic, conceptual level, financial development occurs when financial instruments, markets, and intermediaries mitigate – although do not necessarily eliminate – the effects of imperfect information, limited enforcement, and transactions costs". They provide a richer understanding of the concept of financial development by analyzing it at a multidimensional level and considering four characteristics of financial systems: depth, access, efficiency, and stability, thus providing a comprehensive picture of financial systems' performance.

Many studies have separately analyzed the relationship between financial depth or access and banking competition. Love and Martínez (2015) empirically demonstrate that market power measured with the Lerner and Boone indices hinders access to credit by firms. More recently, Wang et al. (2020) also provide supporting evidence that bank market power imposes obstacles to SMEs' access to finance and boosts their credit constraints. However, no supporting empirical evidence is available for the potential inverse effect of financial access on banking competition. Furthermore, Tan and Floros (2012) point out that more developed banking institutions increase the demand for banking services, which incentivizes potential competitors to enter the market. More recently, Tan (2016) considers both the development of the banking sector and the stock market as industry determinants of banks' performance, obtaining that more developed banks perform higher margins. Moreover, the author argues that the banking sector and the stock market provide feedback to each other since they prompt the development of each sector as they grow together. Therefore, from this literature, more developed financial institutions and markets in a country are expected to correspond to a lower market power for its banks. Furthermore, a positive correlation is expected between the development degree of financial institutions and stock markets.

Third, a significant industry-specific factor influencing banks' performance is capital regulation. The global financial crisis of 2007–09 revealed excessive risk-taking behavior by financial institutions, as well as major deficiencies in market discipline, banking regulation and supervision. Since then, capital requirements have become an important tool for regulatory authorities to promote banks' resilience. The Basel III capital framework developed in 2010 by the Basel Committee on Banking Supervision (BCBS) initiated a series of reforms aimed at raising the quality and quantity of regulatory capital of banks with the purpose of enhancing their risk coverage ability (World Bank, 2019). The Basel III agreement requires banks to build up regulatory minimum capital and to hold two extra capital buffers (capital conservation buffer and discretionary countercyclical buffer) as a cushion to absorb potential losses from capital shocks and to provide a signal of stability to the market.

Regarding the relationship between capital regulation and banking competition, Hackenes and Schnabel (2011) argue that higher capital requirements inhibit competition for loans, prompting an increase in loan rates. Angelini and Cetorelli (2003) look at 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. Demirguc-Kunt et al. (2004) find that restrictive banking regulations, as reserve requirements, considerably increase net interest margins. Thus, given this evidence, we can expect a positive relationship between stricter capital requirements and banks' market power.

Looking specifically at the potential relation between capital buffers and banking competition, the banking literature points out other internal reasons for banks to build up extra equity beyond the capital regulation requirement motives. For instance, accounting for the potential endogeneity between capital buffers and competition, Schaeck and Cihák (2012) find that higher market competition to attract borrowers corresponds to greater incentives for banks to increase capital ratios. They find that a 1% rise in the Panzar and Rosse (1987) H-statistic increases the capital ratio by up to 3.7% for commercial banks. However, Fonseca and González (2010) point 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. More recently, Carvallo and Ortiz (2018) argue that large banks enjoying market power are more risk averse and tend to protect their charter value by holding higher levels of capital. Their results show that banking markets with lower competition levels (by means of the Boone index) tend to have higher capital buffers.

Thus, given the mixed evidence regarding the relationship between capital requirements, capital buffers and competition, this study aims to empirically shed more light on how capital regulation and the level of capital buffers are related to banks' market power.

Moreover, monetary policy constitutes a common object of study in the banking performance literature. Considering the effects of interest policy changes on banks' margins and profitability, the empirical evidence shows mixed results. It remains unclear how banks specifically adjust asset and liability prices in response to monetary policy changes. Most studies find a positive relationship between short-term interest rates and banks' margins (for instance: Bolt et al., 2012; Borio et al., 2015; and Cleassens et al., 2018). However, Alessandri and Nelson (2012) and Busch and Memmel (2015) show different implications depending on the time horizon considered. These authors find that in the short run, a rise in market interest rates harms banks' margins, whereas in the long run, a positive relationship is obtained, which may be the result of differences in the maturity of loans and deposits. Furthermore, the existence of pricing frictions, such as contractual repricing terms, may also condition banks' response to new market rates in the short run. According to Busch and Memmel (2015), 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.

The above literature on monetary policy and banks' performance is tightly related to the underresearched specific relationship between monetary policy and banks' market power. If short-term market interest rates have a systematic effect on banks' margins, a subsequent impact on market power potential seems logical. Following this rationale, Toolsema (2004) provides 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. The author shows that when the policy rate rises, market power (measured by the Lerner index) decreases.

Given the inconclusive evidence on the effects of policy interest rates on banks' profits, no a priori hypothesis regarding the effect of a change in the policy interest rate on banks' market power has been proposed. In this study, the overnight interest rate is selected as a proxy to control for the monetary policy stance since it is widely accepted as the prevailing operational target of monetary policy[4].

3. Methodology

Our model specification is based on the methodology developed by Kumbhakar *et al.* (2012) intended to estimate firm-level market power. This approach has been previously applied to the banking industry by Coccorese (2014), who performs cross-country comparisons of banks' market power using a worldwide dataset of 87 countries. Tsionas *et al.* (2018) employ this model in a system of two nonlinear equations to jointly estimate banks' efficiency and market power. More recently, Karadima and Louri (2020) apply this model to study bank competition and credit risk in the EMU. This paper extends this methodology by incorporating environmental 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. For instance, this model allows market power estimation when input price data are not available. Moreover, it does not require information on output price as required for calculations of the traditional Lerner index; data on total revenue are sufficient. Furthermore, no premise is needed regarding the

[4] According to Nautz and Scheithauer (2011, p. 1375): "Central banks redesigned their monetary policy instruments to ensure that the overnight rate closely follows the central bank's key policy rate and that its volatility remains well contained".

existence of constant returns to scale as when following other NEIO methods or computing the traditional Lerner index.

Kumbhakar *et al.'s* (2012) model starts with the assumption of some degree of market power for profit-maximizing firms. Thus, the output price (*P*) that firms set must be higher than the marginal cost (MC):

$$P > MC \equiv \frac{\partial C}{\partial Y} \tag{1}$$

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

$$P\frac{Y}{C} = \frac{TR}{C} > MC\frac{Y}{C} = \frac{\partial C}{\partial Y}\frac{Y}{C} = \frac{\partial lnC}{\partial lnY} \tag{2}$$

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. Considering the banking industry, a bank's technology can be represented by the following translog total cost function:

$$\ln C = \beta_0 + \sum_{j=1}^{J}\beta_j lnW_j + 0.5\sum_{j=1}^{J}\sum_{k=1}^{K}\beta_{jk} lnW_j \, ln\, W_k + \beta_Y lnY +$$

$$+ 0.5\,\beta_{YY}\,(lnY)^2 + \sum_{j=1}^{J}\beta_{Jy} lnW_j \ln Y \tag{3}$$

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., labor, physical capital and deposits).

Then, the cost-output elasticity ($\partial lnC/\partial lnY$) is equal to:

$$\frac{\partial lnC}{\partial lnY} = \beta_Y + \beta_{YY} lnY + \sum_{j=1}^{J}\beta_{jY} lnW_j \tag{4}$$

Accordingly, inequality (2) can be converted into an equality by adding a nonnegative one-sided term, *u*:

$$\frac{TR}{C} = \frac{\partial lnC}{\partial lnY} + u, \qquad u \geq 0. \tag{5}$$

Then, 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 degree 1 in the price of inputs):

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

(6)

Note that since the term *u* represents the deviations of the revenue share to total cost from its frontier and given that (5) has been 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 ($\frac{TR}{C}$) and its frontier ($\frac{\partial lnC}{\partial lnY} + v$) 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 we 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 ($\frac{\partial lnC}{\partial lnY} + v$) constitutes the frontier itself, where ($\frac{\partial lnC}{\partial lnY}$) is the deterministic component and (*v*) the stochastic term. The nonnegative 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, we are considering the ratio of total revenue share to total cost ($\frac{TR}{C}$) 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 error term.

The estimation procedure continues with the estimation of the parameters in (6) by employing the maximum likelihood (ML) method. This approach 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) consider a half-normal truncated at zero distribution for *u* and a normal distributional form 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 equal to:

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

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), the markup factor θ can be obtained from:

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

(11)

Equation (11) shows that the markup factor (θ) depends on the estimates of u and on the cost-output elasticity estimates. Notably, 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:

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

Therefore, the purpose is to obtain a bank-level value of $\hat{\theta}$ following the above methodology while incorporating the effects of the selected environmental variables, which will affect 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 procedure is to assume that the environmental variables are likely to affect the distribution of the one-sided error term. According to Belotti et al. (2013), these can be incorporated employing three different alternatives: (i) they could shift the frontier and the one-sided error distribution; (ii) they could scale the frontier and the one-sided error distribution; and iii) they could shift and scale 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. One is whether to assume heteroskedasticity in the composite error term. In this regard, Kumbhakar and Tsionas (2008) point out that given that the banking industry is composed of a considerable number of small entities and assets are predominantly concentrated in a few large banks, the variability of both error components is likely different across units. Therefore, 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 consider time-varying or time-invariant technical inefficiency. From the time length of our dataset, time-varying u (u_{it}) seems to be the most convenient choice.

Regarding 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 our model. These authors and other researchers have often employed a two-stage estimation method, first estimating the stochastic frontier model and the technical inefficiency level for each firm and then analyzing how the estimated inefficiency is affected by the exogeneous 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 point 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 line, Kumbhakar, Ghosh, and McGuckin (1991) argue that in the context of stochastic production functions, inconsistent estimates of the parameters will be 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[5].

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

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

(13)

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

Where:

- v_i follows a normal distributional form:

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

- u_i has a truncated-normal distribution (at zero), where $(z'_i\,\delta)$ is the parameterization of the mean distribution of (*u*), (z_i) is the vector of environmental variables and (δ) is the vector of z-parameters:

$$u_{it} \sim N^+\left(z'_{it}\,\delta, \sigma^2_{u_{it}}\right) \qquad (16)$$

$$\mu_i = z'_{it}\,\delta \qquad (17)$$

This parameterization of the mean of (*u*) allows us to analyze how this mean changes with variations in the values of the environmental variables.

[5] See: Kumbhakar (1990), Battesse and Coelli (1992) and Greene (2005).

- ε_{it} is a random disturbance that follows a truncated normal distribution with zero mean and variance σ^2:

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

Thus, this equation system is employed to obtain ML estimations of both technological and contextual parameters.

4. Data and variables

4.1. Databases

The present study employs an unbalanced panel dataset of EU-28 banks spanning the period 2005–2019. Bank-level information for the period 2005–2015 was obtained from the former Bureau Van Dijk's BankScope database, while data corresponding to the period 2015–2019 were collected from the updated version of Moody's Analytics BankFocus database. Both datasets contain bank-specific financial statement information and provide analogous balance sheet items' data. However, with the aim of guaranteeing data homogeneity and comparability, both datasets have been linked by employing the data for the common year (2015). A forward link was applied to the years 2016–2019 to grant a greater influence weight to the part of the sample with most observations (2005–2015). Specifically, a year-link method was applied, which computes a linking factor as the quotient between the newer observation from the BankFocus database and the equivalent older observation in the BankScope database for each bank-level variable and observation in the overlapping year (2015).

All monetary magnitudes are expressed in thousands of dollars, and consolidated financial statements have been considered when possible. We traced the bank history for each individual entity and considered whether any was involved in an M&A during the period of study. We also dropped all banks with inconsistencies or missing values.

Moreover, following Casu et al. (2016), to guarantee that selected banks engage in comparable services, we narrowed our analysis 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 5,930 observations for 756 banks, including only those classified as commercial, cooperative or savings banks. The number of observations is lower than usual compared to those in other empirical studies employing the same database since we selected banks whose identification matched in both databases for the entire period (2005–2019). This constraint is applied since tracing the identity of banks from the BankScope database to BankFocus is not straightforward. A unique identifier that permits the direct traceability of entities is lacking. Thus, a manual review was conducted to select banks that matched accordingly when unifying the same panel of both sources.

Regarding the sources of the environmental 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*. Moreover, bank capital regulation information was collected from the *Financial Stability Board* (*FSB*) publicly available official bank lists on capital requirements. Finally, monetary policy data were collected from both the *European Commission Eurostat Exchange and Interest Rates dataset* and *European Central Bank (ECB) Statistical Data Warehouse*, which provides data on overnight or short-term interest rates for all EU countries.

4.2. Variable descriptions

Regarding the bank-level variables employed in the estimation of the stochastic frontier (equation 13), following standard practice, total revenues (*TR*) are computed as the sum of total interest income and other operating income; total costs (*C*) are 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*) is given by the sum of loans and other interest earning assets. Regarding the input prices, the price of deposits (W_d) is defined as the ratio of interest expenses to total deposits; the price of capital (W_k) is given by the ratio between other operating expenses and fixed assets; and the price of labor (W_l) is proxied by the ratio between personnel expenses and total assets given that information on total employees is not readily available in most observations. Table 1 reports the descriptive statistics for the core variables.

INSERT TABLE 1

Regarding the environmental variables employed in equation (14), *banking market concentration* was controlled, including the Hirschman–Herfindahl index (*HHI*) for total assets. Moreover, financial development variables have been incorporated following the multidimensional approach of Čihák et al. (2012) and the IMF (Svirydzenka, 2016), which offers nine indices to measure the levels of depth, access and efficiency with which financial institutions and financial markets perform for a sample of 183 countries. The indices are presented at three different levels of aggregation. The most disaggregated level is composed of FID, FIA, FIE, FMD, FMA, and FME indices, where the letter I denotes institutions and M markets, and the letters D, A, and E denote depth, access, and efficiency. Note that since the objective of this study is to analyze how the industry-specific environment affects banks' market power, only depth (*FID*) and access (*FIA*) indices are considered proxies for financial institution development[6]. The

[6] Traditionally, banking literature has 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 have

efficiency dimension was excluded from the analysis since it is assessed by employing banks' performance indicators, which are not direct proxies to control for the industry-specific context in each country. Moreover, following Tan (2016), financial markets' development is controlled by its level of magnitude (FMD). *Banks' capital regulation* is approximated by a dummy variable controlling for Global Systemically Important Banks (*G-SIBs*), which is equal to 1 if the bank is listed by the FSB as systemically important and 0 otherwise in any year within the period 2011–2019. In relation to *capital buffers* (*Buffer*), this variable is computed as the difference between the ratio of equity to total assets and the minimum capital adequacy ratio (8%). Moreover, *monetary policy* is controlled by the overnight interest rate or, in the absence of this, the three-month money market interest rate (both defined as *IR*). For EMU countries, the *Euro Over-Night Index Average* (EONIA) is the reference, whereas the reference interest rate for non-EMU members varies from country to country[7] (for instance, 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). Finally, a dummy variable is included to control for the potential impact of *the GFC and Euro sovereign debt crisis* on banks' market power (defined as *Crisis* equal to 1 if the year is within the period 2008–2013 and 0 otherwise). Table 2 summarizes the definitions and sources for these contextual variables.

INSERT TABLE 2

5. Empirical model and estimation results

5.1. Model specification

employed the ratio of private credit to GDP as a proxy for depth (see, for example: De Gregorio and Guidotti, 1995; Arcand et al., 2012; Caporale et al., 2014; 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 analyzed sample.

From the methodology described in Section 3, the model specification (named BC95(1)), which includes the environmental variables, is as follows:

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

(19)

$$u_{it} = \delta_0 + \delta_1 \ (IR * EMU)_{it} + \delta_2 \ (IR * NOEMU)_{it} + \delta_3 FIA_{it} + \delta_4 FID_{it} + \delta_5 \ FMD_{it} + \delta_6 \ (HHI * EMU_{it}) + \delta_7 \ (HHI * NOEMU)_{it} + \delta_8 \ Buffer_{it} + \delta_9 \ (GSIB * Buffer)_{it} + \delta_{10} \ crisis_{it} + \varepsilon_{it}$$

(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 normalized by the price of labor (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 and Mester, 1993; Mester, 1996).

Equation (20) includes a set of exogenous environmental 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).

INSERT TABLE 3

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 eurozone countries, reflecting 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*) are introduced in the model: the first term involves multiplying (*IR*) by a dummy variable defined as "EMU", which is equal to one if the bank belongs to an EMU country, and the second term involves multiplying (*IR*) by a dummy "non-EMU", which is equal to one if the bank belongs to a non-EMU country, which allows us 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 show 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 show that both groups of countries present 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 (*G-SIB*buffer*) is also included to provide information on how extra capital requirements directed to G-SIBs may affect their level of market power.

Finally, since no direct causality from concentration to competition has been 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 institutional environment, two interaction terms for (*HHI*) have been included to separately analyze its effect on banks' markup.

5.2. ML estimation results

Table 4 exhibits the ML results for simultaneous estimation of the frontier and the one-sided error term *u* following the Battese and Coelli (1995) methodology. For comparison purposes and to analyze the extent to which the chosen environmental variables contribute to the final estimation of the Lerner index, a second ML estimation without considering environmental variables was conducted (named BC95(2)). This model follows the same estimation procedure with an identical specification for the frontier (equation (19)), although the set of environmental variables in equation (20) is replaced with a time trend variable (*T*) to allow banks' markup to evolve over time.

INSERT TABLE 4

Table 4 shows that all coefficients from the stochastic frontier (equation (19)) are highly significant and present the expected signs in both the BC95(1) and BC95(2) models. Moreover, all environmental variables in BC95(1) are also significant at the 5% confidence level, except for the interaction term (*G-SIB*Buffer*), which is significant at the 10% confidence level. The estimation results suggest a negative short-term relationship between the operational target of monetary policy (IR) and banks' markup for both groups of countries (EMU and non-EMU). This finding is related to the evidence presented by Busch and Memmel (2015), who find that in the short run, an increase in policy rates translates into lower margins.

The effect of financial institutions' development presents the expected negative sign when accessibility is considered. In line with those of Tan and Floros (2012), this result shows that more accessible financial institutions (*FIAs*) (proxied by the number of bank branches and ATMs per 100,000 adults) correspond to lower markups. However, when looking at the effect of financial institutions' depth, magnitude favors market power. The results show that a higher magnitude of EU financial institutions' markets compared to each country's GDP corresponds to higher market power. Moreover, the results show that the magnitude of stock markets (*FMD*) (proxied by stock market capitalization to GDP, stocks traded to GDP, among others) presents a negative relationship with the markup on interest-earning assets.

Furthermore, the significance of the coefficients for both interaction terms (*HHI*EMU* and *HHI*NoEMU*) reveals that market concentration affects the capacity of banks to exercise market power, although the sign of the effect cannot be generalized. Divergences in the effect of market concentration are detected among EU countries. For EMU banks, the results indicate that more concentrated total assets in the EMU banking market correspond to lower bank markups. Nonetheless, a higher market concentration in non-EMU countries favors banks' market power.

Notably, 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*Buffer*) indicates that for global systematically important banks, an increase in their level of capital buffer is highly and significantly related to higher markups. Finally, as expected, both the global financial crisis of 2008 and the European debt crisis in 2011 negatively affected the markup levels of banks throughout their courses.

Tables 5 and 6 report the posterior means of the Lerner index and the cost elasticities obtained from models BC95(1) and BC95(2), respectively. First, regarding the cost elasticity estimates, EU banks in the sample operate at increasing returns to scale. These results are consistent with the empirical findings on economies of scale for EU banks for the period 2000–2011 (see Dijkstra, 2013 and Beccalli et al., 2015). Second, comparing the results exhibited in Tables 5 and 6, the mean Lerner index estimates suggest that if environmental conditions are considered, Lerner index estimates are significantly leveled down for the whole sample (EU) and for each subgroup of countries separately. These differences may indicate that Lerner index estimations for banks carried out without controlling for the environmental conditions of their respective countries may be biased. Furthermore, the mean Lerner index estimates show that non-EMU banks have enjoyed, on average, higher levels of market power.

INSERT TABLES 5 AND 6

Considering the Lerner index evolution over time, Figure 1 reveals that when controlling for the environment, the mean Lerner index estimations are leveled down for the entire period of study in the whole sample (EU) and in each subgroup (EMU and non-EMU). Furthermore, since 2008, an upward trend in market power is revealed for the whole sample (EU), and the evidenced rise in market power since 2013 is significantly boosted when environmental conditions are considered.

INSERT FIGURE 1

Interestingly, when environmental variables are not considered, Figure 1.2 suggests a tendency toward market power deterioration in EMU countries for the whole period of study. However, if environmental conditions are included, the observed market power deterioration disappears, suggesting that when environmental variables are not considered, the apparent loss in market power may hide environmental effects on market power. When these effects are controlled, no trend of market power deterioration is revealed. However, a downward trend in EMU banking market power is obtained from 2014, which may be explained by the steps taken by the European Banking Union since 2012.

For non-EMU banks (Figure 1.3), the inclusion of environmental conditions significantly boosts the witnessed upward trend in market power, also notably enhancing the increase found from 2013 onwards. This finding reveals that the upward trend in the Lerner index for EU banks is mainly driven by the non-EMU group of banks. Finally, the inverse trend in the market power evolution between EMU and non-EMU countries since 2013 should be noted. The results reveal that from this year on, EMU banks' market power has slightly decreased and stabilized, whereas in non-EMU banks, an upward trend is evident.

5.3. Mean Lerner index estimations by countries

Table 7 and Figure 2 provide the average Lerner index estimations, controlling for the environment, for each country and the whole period (2005–2019), along with the SD and minimum and maximum levels. The lowest mean Lerner index estimations correspond to Belgium (0.09), followed by Portugal (0.10). In contrast, the highest mean Lerner index estimation is obtained in Estonia (0.31), followed by the Czech Republic (0.27).

INSERT TABLE 7

INSERT FIGURE 2

By more deeply analyzing the evolution of the Lerner index estimation with environmental variables, some important considerations can be suggested. Figure 3 shows that the market power of *EMU banks* was permanently lower than *that of non-EMU banks* for the whole study period. Second, both the global crisis of 2008 and the sovereign debt crisis of 2011 negatively affected the Lerner index for the two groups of countries. In the beginning years of both crises, competition levels increased in all EU banking markets, which was followed by a notable increase in market power levels in subsequent years, as reported by other empirical studies such as Jonghe et al. (2016). Third, although the disparities in market power have been persistent between *EMU* and *non-EMU banks* since 2005, these differences have markedly increased since 2013 as a consequence of the significant increase in market power levels in non-EMU countries in conjunction with a decrease in stability for EMU members.

INSERT FIGURE 3

To obtain further information on the reasons behind the sharp rise in market power in non-EMU countries, the evolution of the mean Lerner index is investigated for three subgroups of non-EMU countries: *Central-Eastern* (composed of Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Latvia, Poland, Romania, Slovakia, and Slovenia), *Nordics* (including Denmark, Norway and Sweden) and *UK* (the United Kingdom). Given the different geographical and institutional differences among these groups of countries, potential divergence trends could be detected in banking market power for these markets.

INSERT FIGURE 4

Figure 4 shows the evolution of Lerner index estimates for the three groups of non-EMU countries along with the previously estimated EMU series. The graph shows that the increase in market power observed for non-EMU countries is primarily explained by the marked increase in market power driven by UK and Nordic banks. In Central-Eastern non-EMU countries, a certain trend of market power stability is detected for the 2014–2019 subperiod.

5.4. Lerner index disparities among groups of EU banks

In light of these findings, an interesting research question is whether the dispersion in the cross-sectional distribution of the Lerner index increases over time. To study disparities in banks between and within the two groups of countries, the evolution of the dispersion of the Lerner index over the study period was analyzed. With this aim, the coefficient of variation (CV) was employed as a convergence indicator. Table 8 presents the results of the CV calculations for each group of countries, and its evolution is depicted in Figure 5.

INSERT TABLE 8

INSERT FIGURE 5

The evolution of the CV for EU banks shows a clear tendency to diverge considering the whole period of study. On the one hand, market power within EMU countries converged since 2008 and until the beginning of the debt crisis in 2011, when disparities among EMU banks increased again. On the other hand, the calculated CV for non-EMU banks has been almost constant since 2012, although a weak divergence process is witnessed within this group for the whole period of study. However, in contrast to EMU banks, a divergence process in market power is observed during the course of the global financial crisis (2008–2011). As Figure 6 shows, this process of divergence is mainly driven by the groups of UK and Nordic banks. These groups of banks show a sharp increase in disparities in estimated market power in the 2008–2011 period. Finally, looking at the CV for the whole sample of EU countries, its evolution indicates an increasing divergence trend for market power between EMU and non-EMU banks. Fragmentation in competition is especially evident from 2012 onward, when non-EMU banks' market power substantially increased.

INSERT FIGURE 6

6. Conclusions

To assess the EU banking competition setting, analyzing how different environmental conditions among EU members could affect the ability of banks to exercise market power is important. This paper aims to provide market power estimations for EU banks for the period 2005–2019 controlling for the effect of regulatory, economic policy, and market conditions (among other factors) with a known influence on banks' performance. To achieve this, estimates of the Lerner index are obtained by employing maximum likelihood (ML) estimation of the stochastic frontier model of market power developed by Kumbhakar *et al.* (2012) and incorporating the effect of environmental variables by utilizing the Battese and Coelli (1995) model specification. The inclusion of environmental variables sets banks' *playing field* for proper cross-country comparisons of market power. Specifically, the analysis includes environmental conditions that constitute different scopes outside the intrinsic banking business: (i) monetary policy, (ii) EU bank capital regulation, (iii) the degree of financial system development, (iv) market structure and (v) economic shocks.

The estimation results reveal that when environmental conditions are considered, the estimated mean Lerner index for the whole sample of EU banks is leveled down compared to nonenvironmentally controlled Lerner index estimates. Furthermore, the results show a notable divergence in market power levels between EMU and non-EMU banks for the whole period of study (2005–2019). On average, non-EMU banks have enjoyed higher levels of market power, with the highest average levels belonging to Sweden (0.24), the Czech Republic (0.22) and Bulgaria (0.21); in comparison to EMU members, where Finland (0.03), the Netherlands, and Malta (0.04) have the lowest Lerner index estimations. Moreover, a sharp increase in market power levels has been detected for EU banks since 2012. This upward trend in banks' market power was mainly driven by the marked increase in the estimated Lerner index for the non-EMU group of banks, particularly UK and Nordic banks. These reasons explain the intensified disparities between EMU and non-EMU banks since 2012, showing a clear process of divergence among EU banks.

From these findings, the importance of including environmental variables when estimating banks' market power should be noted. First, including these variables allows us to obtain a "cleaner" picture of the competitive scenario given that by controlling for industry-specific and external macroeconomic factors, differences in market power levels among countries can be attributed to internal bank characteristic divergences instead of potential concealed environmental differences. Second, results also show the relationship between each environmental dimension and banks' market power. For instance, estimation results suggest a negative short-term relationship between the short-term operational target of monetary policy and banks' market power for both groups of countries (EMU and non-EMU). Moreover, the analysis reveals that market structure is still relevant to the ability of banks to exercise market power, although a significant divergence of its effect is evident among EU countries. For EMU banks, a more concentrated EMU banking market corresponds to lower bank markups. Nonetheless, a positive relationship is found between market concentration and market power in non-EMU countries. This reveals that concentration measures are not a proper direct indicator of conduct, although it seems relevant when conducting cross-country analyses given that its effect may inversely condition banks' performance depending on the group of countries analyzed.

Furthermore, estimation results show weak but constant deterioration of banking market power levels within EMU countries since 2014, which may be regarded as an indication of advances in the banking union. However, within EMU banks, the convergence analysis revealed a clear pattern of divergence in market power indices, which works against the logic of banking market integration. Thus, the existence of persistent barriers to the integration of the EMU banking market must not be disregarded.

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Table 1. Definitions and descriptive statistics of the key variables employed in the frontier estimation.

Variable name	*Description*	*Mean*	*Std. Deviation*
TR	Total revenue (1)	3,733	9,848
C	Total cost (1)	4,049	10,800
RC	Revenue to cost ratio (= TR/C)	1.11	0.31
Y	Total output (1)	118,000	328,000
$\boldsymbol{W_d}$	Price of the deposit ratio	0.03	0.03
$\boldsymbol{W_l}$	Price of the labor ratio	0.02	0.01
$\boldsymbol{W_k}$	Price of the capital ratio	4.53	41.32
E	Total equity (1)	6,511	16,800

Note: (1): million U.S. dollars. Number of observations: 5930. Number of banks 756. Source: BankScope and BankFocus databases.

Table 2. Environmental variables considered.

Variable name	*Description*	*Source*
HHI	Hirschman–Herfindahl index (HHI) for total assets	ECB Banking Structural Financial Indicators Database
FID	Financial Institutions' Depth Normalized 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 Normalized 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 Normalized 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)
G-SIB	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.
Crisis	Global Financial Crisis and Euro Sovereign Debt crisis: dummy variable equal to 1 if the year is 2008–2013 and 0 otherwise.	Own elaboration

Table 3. Sample statistics of the variables in equations (13) and (14).

Sample	EU banks (whole sample)				EMU banks				Non-EMU banks			
Variables	**Mean**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**
Revenue to cost ratio (RC)	1.11	0.35	0.06	4.69	1.05	0.30	0.06	3.88	1.26	0.40	0.15	4.69
ln Total output (ln Q)	16.43	2.09	7.79	22.11	16.63	1.97	10.56	21.53	15.99	2.28	7.79	22.11
ln Price of the deposit ratio (ln Wd)	0.78	1.09	-4.65	5.36	0.86	1.05	-4.65	5.28	0.60	1.15	-3.53	5.36
ln Price of the capital ratio (ln Wk)	4.88	1.32	-0.87	15.60	4.83	1.22	1.26	13.06	5.00	1.52	-0.87	15.60
ln Equity (ln E)	14.03	1.87	8.68	19.11	14.12	1.80	8.23	18.67	13.67	2.02	7.02	19.11
Interaction term: (IR*EMU)	0.8	1.33	-0.39	3.87	1.09	1.45	-0.39	3.87	0.00	0.00	0.00	0.00
o Overnight/short-term interest rate (IR)	1.37	1.81	-0.58	11.17	1.09	1.45	-0.39	3.87	2.02	2.31	-0.58	11.17
o EMU (= 1 if the bank belongs to an EMU country)	0.69	0.46	0	1	1	0	1	1	0	0	0	0
Interaction term: (IR*NoEMU)	0.63	1.64	-0.58	11.17	0.00	0.00	0.00	0.00	2.42	2.46	-0.58	11.17
o Overnight/short-term interest rate (IR)	1.44	1.86	-0.58	11.17	1.09	1.45	-0.39	3.87	2.42	2.46	-0.58	11.17
o NoEMU (= 1 if the bank belongs to a non-EMU country)	0.31	0.46	0	1	0	0	0	0	1	0	1	1
Financial Institution Access (FIA)	0.77	0.19	0.16	1	0.82	0.18	0.16	1.00	0.65	0.16	0.30	0.93
Financial Institution Depth (FID)	0.61	0.22	0.13	1	0.63	0.15	0.19	0.99	0.57	0.33	0.13	1.00
Financial Market Depth (FMD)	0.64	0.28	0.03	0.99	0.71	0.21	0.04	0.99	0.45	0.35	0.03	0.99
Interaction term: (HHI*EMU)	0.06	0.06	0	0.39	0.08	0.06	0.02	0.39	0.00	0.00	0.00	0.00
o Herfindahl-Hirschman index for total assets (HHI)	0.08	0.06	0.02	0.4	0.08	0.06	0.02	0.39	0.10	0.09	0.04	0.46
Interaction term: (HHI*NoEMU)	0.03	0.05	0	0.4	0.00	0.00	0.00	0.00	0.10	0.09	0.04	0.46
o Herfindahl-Hirschman index for total assets (HHI)	0.08	0.06	0.02	0.4	0.08	0.06	0.02	0.39	0.10	0.09	0.04	0.46
Capital Buffer (Buffer) (Equity/Total Assets) – 8%	0.01	0.06	-0.08	0.84	0.01	0.06	-0.08	0.84	0.02	0.06	-0.07	0.60
Interaction term: (G-SIB*Buffer)	0.01	0.08	-0.05	0.09	0.00	0.01	-0.05	0.10	0.00	0.01	-0.05	0.09
o G-SIB (= 1 if the bank is Global Systemically Important)	0.06	0.24	0	1	0.06	0.22	0	1	0.07	0.26	0	1
o Capital Buffer (Buffer) = (Equity/Total Assets) – 8%	0.01	0.06	-0.08	0.84	0.00	0.01	0.06	-0.08	0.02	0.06	-0.07	0.60
Crisis (= 1 if the observation belongs to the period 2008–2013)	0.24	0.43	0	1	0.25	0.44	0	1	0.22	0.41	0	1
Total number of observations in the sample	5930				4094				1836			

Table 4: Estimation results of the ML random-effects (truncated normal) frontier models.

Variables	**Model BC95 (1) (with environmental variables)** Coefficient (St. dev.)	z-Statistic	**Model BC95 (2) (without environmental variables)** Coefficient (St. dev.)	z-Statistic
Stochastic Frontier				
Ln Q	-0.09*** (0.01)	-11.71	-0.13*** (0.01)	-15.96
Ln Wd	-0.05*** (0.00)	-11.83	-0.06*** (0.01)	-14.10
Ln Wk	-0.03*** (0.00)	-8.54	-0.02*** (0.00)	-4.83
Ln E	0.10*** (0.04)	12.85	0.14*** (0.01)	16.76
Constant	1.11*** (0.03)	34.15	1.03*** (0.04)	29.25
Mu (u)				
IR*EMU	-0.95** (0.43)	-2.24	-	-
IR* No-EMU	-0.56** (0.23)	-2.47	-	-
FIA	-4.65** (1.94)	-2.41	-	-
FID	9.75*** (3.55)	2.75	-	-
FMD	- 10.04*** (3.64)	-2.76	-	-
HHI*EMU	-20.83** (8.34)	-2.50	-	-
HHI*No-EMU	8.21*** (2.82)	2.91	-	-
Buffer	16.95*** (5.11)	3.32	-	-
G-SIB*Buffer	36.33* (20.67)	1.76	-	-
Crisis	-3.94*** (1.43)	-2.76	-	-
Constant	-4.78** (2.10)	-2.28	-	-
T (time trend)	-	-	0.02* (0.01)	1.82
Usigma				
Constant	0.75** (0.35)	2.13	-1.98*** (0.05)	-37.35
Vsigma				
Constant	-3.11*** (0.03)	-105.28	-3.16*** (0.04)	-77.32
Sigma_u	1.46*** (0.25)	5.64	0.37*** (0.01)	38.21
Sigma_v	0.21*** (0.01)	67.78	0.21*** (0.00)	48.94
Lambda	6.89*** (0.26)	26.67	1.80*** (0.01)	148.05
Log Likelihood	-787.06		-1,350.15	
Wald Chi	687.58	p value (0.00)	909.80	p value (0.00)

Note: (1): Estimates were obtained by employing the ML method for simultaneous estimation of the parameters of the frontier and direct markup "*Mu (u)"*. The truncated normal specification assumptions of Battese and Coelli (1995) are applied. Dependent variable: Revenue to cost ratio. Common sample. Number of observations: 5235. Number of banks 705. *, **, and *** represent significance at 10% (p<0.1), 5% (p<0.05), and 1% (p<0.01), respectively.

Table 5. Posterior mean estimates of the Lerner Index and scale elasticities from the model with environmental variables included (BC95(1)).

Estimated Lerner Index	**Total sample**	**EMU**	**Non-EMU**
Number of observations	5,930	4,094	1,836
Mean	**0.16**	**0.13**	**0.22**
Estimated cost elasticity (1)	***Total sample***	***EMU***	***Non-EMU***
Number of observations	5,930	4,094	1,836
Mean	**0.92**	**0.91**	**0.93**

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).

Table 6. Posterior mean estimates of the Lerner index from the model without environmental variables (BC95(2)).

Estimated Lerner Index	**Total sample**	**EMU**	**Non-EMU**
Number of observations	5,930	4,094	1,836
Mean	**0.26**	**0.24**	**0.29**
Estimated cost elasticity (1)	***Total sample***	***EMU***	***Non-EMU***
Number of observations	5,930	4,094	1,836
Mean	**0.81**	**0.80**	**0.83**

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).

Table 7. Estimated mean Lerner index by country (from model BC95(1)) over the period 2005–2019.

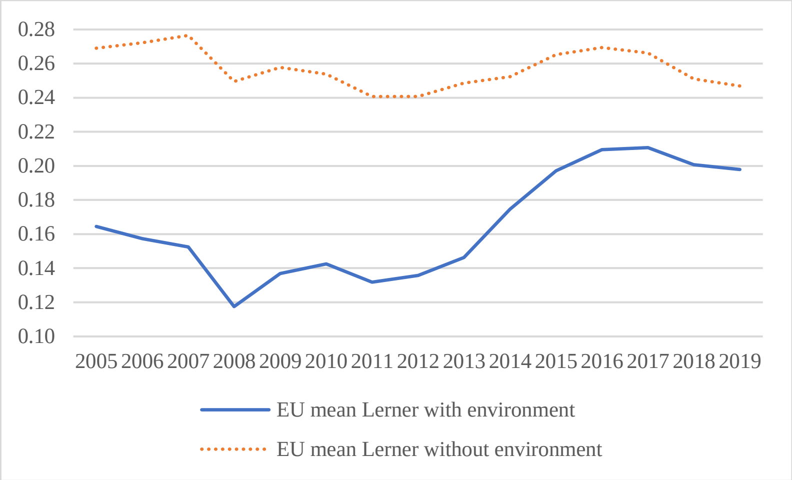
Country	***Observations***	***Mean***	***Std. Dev.***	***Min***	***Max***
AUSTRIA	261	0.14	0.06	0.05	0.47
BELGIUM	108	0.09	0.04	0.04	0.25
BULGARIA	112	0.26	0.13	0.05	0.63
CROATIA	31	0.19	0.08	0.08	0.45
CYPRUS	68	0.16	0.05	0.07	0.34
CZECH REPUBLIC	104	0.27	0.13	0.04	0.66
DENMARK	289	0.21	0.10	0.05	0.60
ESTONIA	66	0.31	0.15	0.06	0.61
FINLAND	107	0.12	0.06	0.06	0.34
FRANCE	1,149	0.12	0.05	0.03	0.52
GERMANY	425	0.14	0.07	0.05	0.70
GREECE	117	0.12	0.05	0.04	0.41
HUNGARY	104	0.16	0.06	0.08	0.37
IRELAND	77	0.19	0.08	0.06	0.51
ITALY	517	0.14	0.07	0.04	0.71
LATVIA	161	0.22	0.12	0.03	0.58
LUXEMBOURG	104	0.12	0.07	0.05	0.39
MALTA	55	0.19	0.09	0.08	0.52
NETHERLANDS	210	0.12	0.06	0.04	0.37
POLAND	208	0.16	0.05	0.04	0.39
PORTUGAL	166	0.10	0.05	0.05	0.46
ROMANIA	92	0.17	0.08	0.06	0.38
SLOVAKIA	84	0.18	0.08	0.05	0.47
SLOVENIA	98	0.18	0.07	0.06	0.53
SPAIN	539	0.12	0.05	0.04	0.58
SWEDEN	120	0.26	0.15	0.06	0.72
UNITED KINGDOM	558	0.23	0.14	0.03	0.83

Table 8. Coefficient of variation (CV) (in %) of the Lerner index estimation by groups of banks.

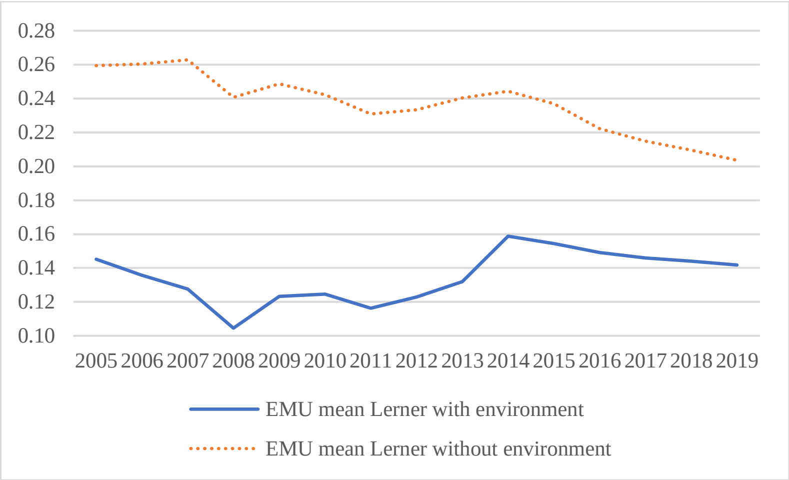
Year	EU banks	EMU banks	Non-EMU banks
2005	50.3	48.4	44.5
2006	53.5	50.8	45.6
2007	53.5	46.7	46.4
2008	52.1	51.1	44.3
2009	50.0	45.9	48.1
2010	53.1	43.8	53.0
2011	53.5	43.9	54.7
2012	51.4	47.4	49.7
2013	54.6	53.5	49.4
2014	53.3	52.2	48.4
2015	60.8	54.9	51.9
2016	65.2	58.3	49.4
2017	68.6	58.6	52.5
2018	66.6	59.9	51.9
2019	68.0	62.9	52.6

Figure 1. Evolution of the estimated Lerner index: sample means obtained controlling for the environment (model BC95(1)) and without environmental variables (model BC95(2)).

1.1. Mean Lerner index for EU banks



1.2. Mean Lerner index for EMU banks



1.3. Mean Lerner index for non-EMU banks

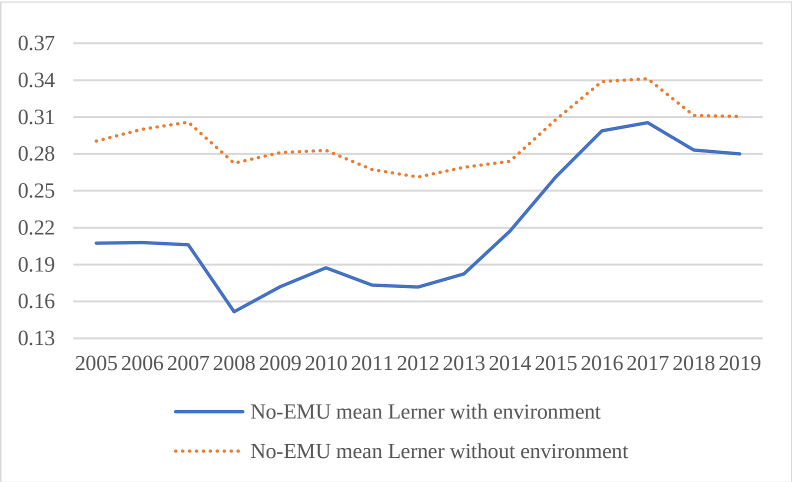


Figure 2. Mean Lerner index estimation with environmental variables by country.

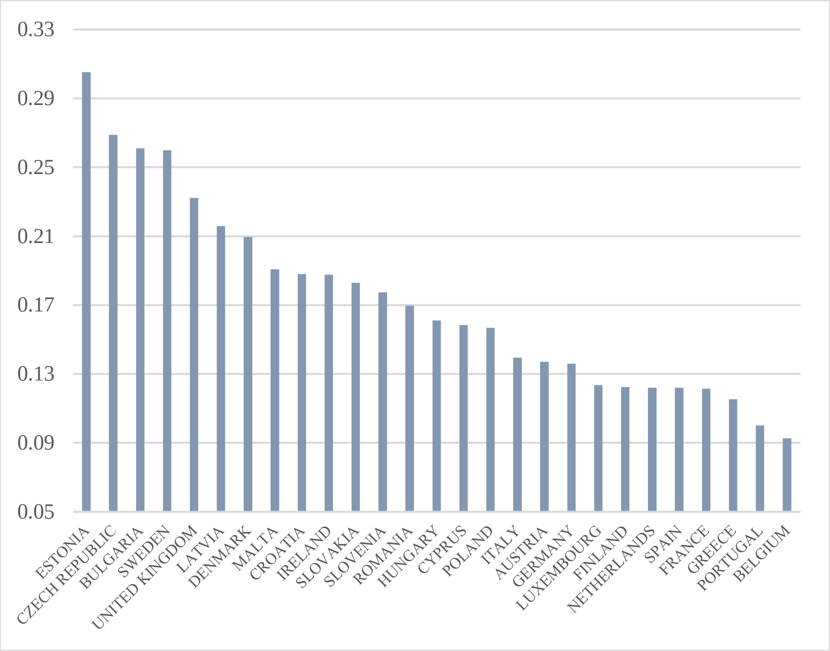


Figure 3. Mean Lerner index estimation with environmental variables by group of banks.

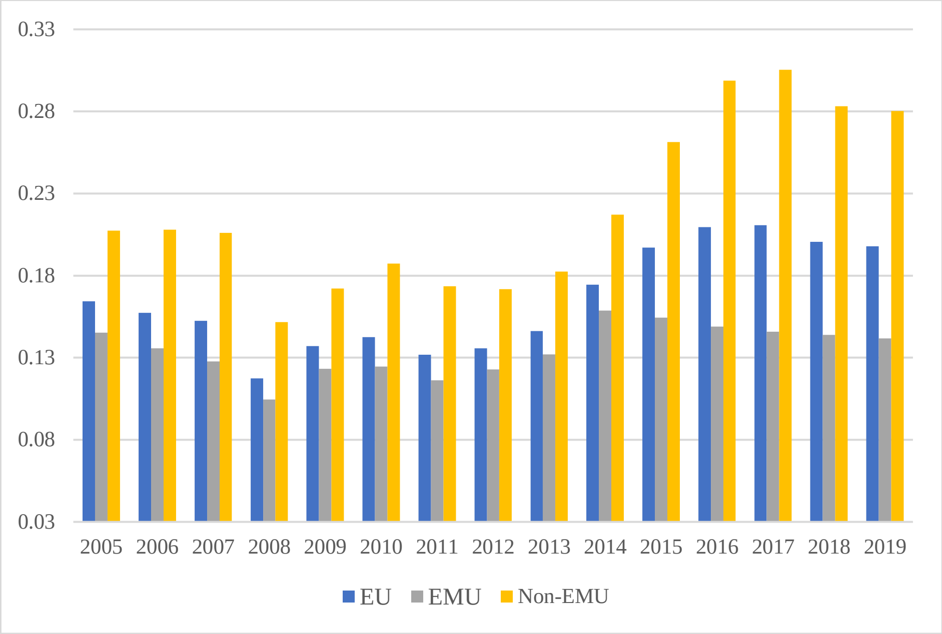


Figure 4. Mean Lerner index estimation with environmental variables by group of non-EMU banks.

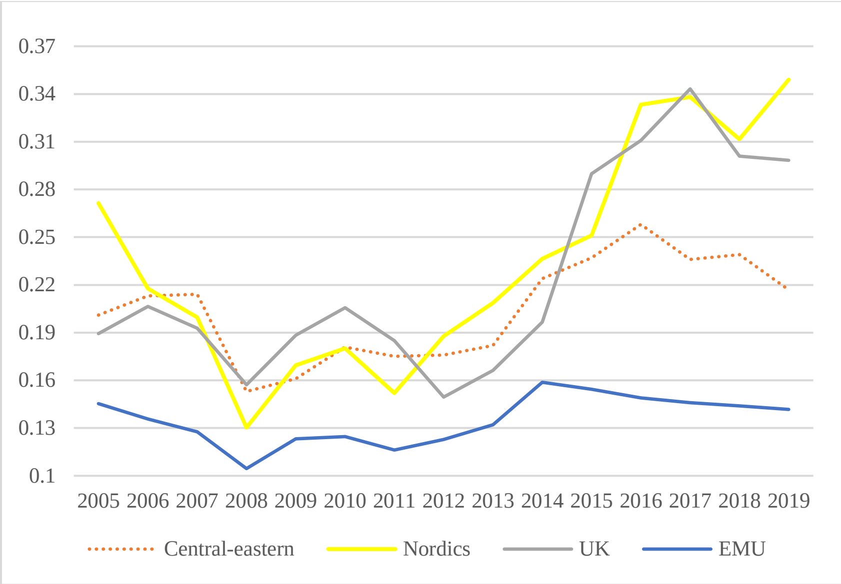


Figure 5. Coefficient of variation (CV) of the Lerner index estimation by group of EU banks.

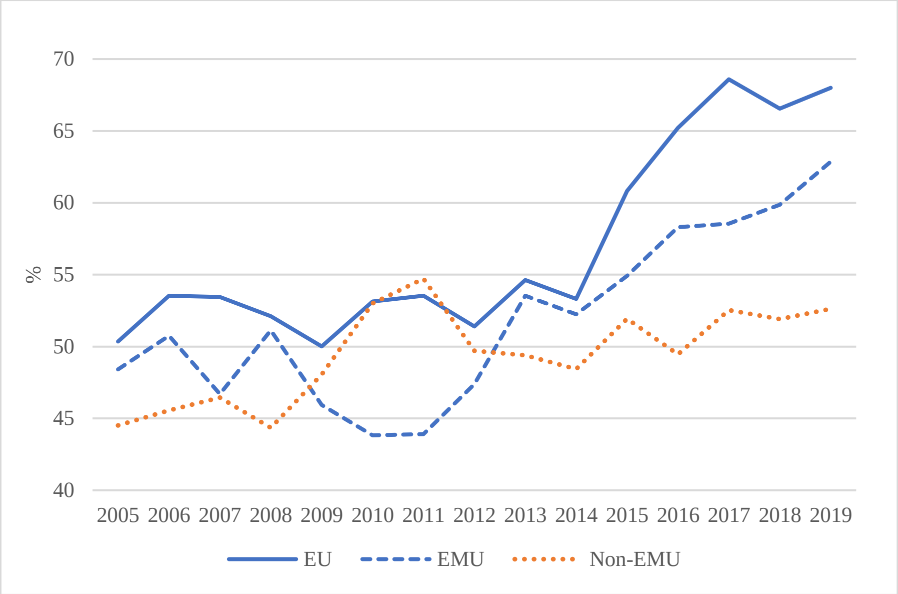


Figure 6. Coefficient of variation (CV) of the Lerner index estimation by group of banks.