Does Competition Lead to Efficiency? The Case of EU Commercial Banks

Barbara Casu[†]
Cass Business School, City University
b.casu@city.ac.uk

Claudia Girardone[‡]
University of Essex
cgirardone@essex.ac.uk

Abstract

In Europe, the past twenty years saw a process of liberalisation, deregulation and unprecedented financial sector reform whose main aims were to increase competition and remove all remaining barriers to the integration of EU banking sectors. However, the recent acceleration in the consolidation process has raised concerns about the potential implications for public policies deriving from increased market power. Using bank level balance sheet data for commercial banks in the major EU banking markets, this paper aims to shed some light on the recent developments in competition, concentration and bank-specific efficiency levels. Furthermore, using a Granger-type causality test estimations, this study aims to investigate the relationship between competition and efficiency in banking markets. Our findings suggest a negative causation between efficiency and competition, whereas the causality running from competition to efficiency, although positive, is relatively weak.

Keywords: Competition, Efficiency, Market Power, Granger Causality, EU Commercial Banks.

JEL classification: G21; D24

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[†] Barbara Casu, Faculty of Finance, Cass Business School, City University, 106 Bunhill Row, London EC1Y 8TZ, UK. Tel. +44 (0) 207 0405283 or email: b.casu@city.ac.uk

[‡] Claudia Girardone, School of Accounting, Finance and Management, University of Essex, Wivenhoe Park, Colchester, CO4 3SQ. Tel. +44(0) 1206 87 4156 or email: cgirardone@essex.ac.uk

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1. Introduction

Competition is generally accepted as a positive force in most industries; it is supposed to have a positive impact on an industry's efficiency, quality of provision, innovation and international competitiveness. The past twenty years saw a process of liberalisation, deregulation and unprecedented financial sector reform both in developing and developed countries. In the European Union, the aim of regulatory developments, which include movements towards the creation of a single market for financial services, was to foster competition in order to improve the productivity, efficiency and profitability of the banking systems and also to increase both national and international competitiveness. The European Commission (EC), in its recent White Paper on Financial Services Policy (2005-2010) has stated that its principal objectives include: "*To consolidate dynamically towards an integrated, open, inclusive, competitive, and economically efficient EU financial market and to remove the remaining economically significant barriers so financial services can be provided and capital can circulate freely throughout the EU at the lowest possible cost*…" (SEC(2005) 1574). The EC believes that the aim of increased financial integration has been driven forward by the success of the Financial Services Action Plan 1999-2005 (FSAP), resulting in improvements in the financial industry's overall performance: higher liquidity, increased competition, sound profitability and stronger financial stability. The EC is also keen to further enhance competition to encourage additional consolidation and to boost the efficiency of pan-European financial markets.

Banks responded to the new operating environment by adapting their strategies, seeking new distribution channels and changing their organisational structures. Increased competition has also been considered the main driving force behind the acceleration in the recent consolidation process; which is raising concerns about increased concentration in the banking sector and its potential implications for public policy. The aggregate number of credit institutions continued declining, confirming the trend of market consolidation. At the end of 2005, there were 8,684 institutions representing a decrease of 10.9% relative to 2001. Consolidation has proceeded even faster in the euro area with a decrease of 12.5% since 2001 (ECB, 2006). In past years, concentration operations in the EU banking sector have been predominantly of a domestic nature. Between 1993 and 2003, the number of mergers and acquisitions involving domestic credit institutions represented about 80% of total consolidation activity in the EU (Walkner and Raes, 2005). However, the pace of domestic consolidation has recently slowed down, whereas the value of cross-border bank M&A has been rising, reaching record levels in 2005. Since the mid-1990s European banks have spent €158bn on 274 cross-border M&A deals, involving other European banks and there are reasons to believe the trend will gather pace (PWC, 2006). As a consequence, the degree of concentration of EU banking systems continues to rise: in the period 2000-2005 the five largest credit institutions increased their share of total assets from 37.8% to 42.3% in the EU (from 39.1% to 43% in the euro area) (ECB, 2006).

The impact of consolidation on banking sector efficiency and performance remains controversial (see Amel et al., 2004). In particular, the debate on the competition and market power effects of bank concentration, and their relationship with profitability and efficiency issues, has raised great interest among academics, policy-makers and anti-trust authorities. Traditionally, research and public policy concerns have focused on the social loss (higher prices and restricted output) associated with the exercise of market power in concentrated markets. This is known as the "quiet life hypothesis" observed by Hicks (1935). Berger and Hannan (1998) posit that, in addition to the social loss associated with the "quiet life", the exercise of market power may also induce higher social costs because it may lessen the effort by managers to operate efficiently. Indeed, these issues are highly interrelated and often intertwined and, given the unique role of banks in the economy and the potential non-trivial implications for welfare, they deserve special attention.

The study of bank competition and its effect on the concentration, efficiency, profitability of the EU banking sector is therefore of relevance in a period of renewed regulatory efforts to remove the remaining barriers and of increased domestic and cross-border M&As. This paper aims to investigate the dynamics of both competition and efficiency in EU banking markets since the year 2000. Focusing on the commercial banking sector of the five main EU banking markets (France, Germany, Italy, Spain and the UK), this study evaluates cost efficiency using both parametric (SFA) and non parametric (DEA) approaches. We also test the degree of competition by using both structural and non-structural methods. Finally, using dynamic panel data Granger-type causality test estimations, this study aims to further the existing literature by directly investigating the relationship between competition and efficiency in banking markets. Whereas a positive relationship between competition and efficiency is often assumed, the specific characteristics of banking markets (i.e. entry barriers, sunk costs, information asymmetries) may lead to excessive market power of efficient banks, therefore reducing competition. Our findings suggest a negative causation between efficiency and competition, whereas the causality running from competition to efficiency, although positive, is relatively weak. Our results are robust with respect to the use of two different methods for measuring bank efficiency (SFA and DEA). These findings pose further questions for European regulators, as they might be faced by a trade-off between competition and efficiency.

The remainder of the paper is structured as follows. Section 2 reviews the main literature on competition and efficiency in banking. Section 3 describes data and empirical methods used. Section 4 discusses the results and Section 5 concludes.

2. Competition and Efficiency in European Banking

Over the past twenty years, the deregulation and market integration processes, coupled with advances in information technologies, have been a steady feature of EU banking markets and have given way to a profound transformation and restructuring of the banking industry, which materialised in enhanced consolidation and a move away from the traditional intermediation business into more profitable investment services. The analysis of the relationship connecting deregulation, market enlargement, competition, consolidation, profitability and efficiency is one of relevance to researchers and policymakers.

The standard economic argument for the positive influence of competition on firms' performance is that the existence of monopoly rents gives managers the potential of capturing some of them in the form of slack or inefficiency (see Nickell et al., 1997). Competition (or lack of it) is normally proxied by increased concentration, which leads to producers' surplus and non-competitive pricing. The existence of a link between market structure and efficiency was first proposed by Hicks (1935) and the "quiet life hypothesis". Hicks (1935) argued that monopoly power allows managers a quiet life free from competition and therefore increased concentration should bring about a decrease in efficiency. Leibenstein (1966) argued that inefficiencies are reduced by increased competition as managers respond to the challenge. Berger and Hannan (1998) relate the impact of market structure on efficiency to several related reasons: (1) high levels of market concentration may allow firms to charge prices in excess of competitive levels and allow manages to benefit from higher prices not necessarily as higher profits but as "quiet life" (i.e. they do not need to work hard to keep costs under control); (2) market power may allow managers to pursue objectives other than firm profits; (3) management may use resources to obtain and maintain market power; and (4) the higher prices charged when exploiting market power allow inefficient managers to persist. Berger and Hannan (1998) conclude that market power may allow for managerial incompetence to persist and therefore negatively impact cost efficiency. However, these explanations assume that the traditional Structure-Conduct-Performance (SCP) paradigm holds, at least partially. In the traditional industrial organisation literature, the SCP hypothesis is essentially based on the assumption that concentration weakens competition by fostering collusive behaviour among firms (the so-called "collusion hypothesis"). Increased market concentration was found to be associated with higher prices and greater than normal profits (Bain, 1951). However, several banking studies suggest that concentration does not substantially increase bank profitability (Berger, 1995) as predicted by the SCP hypothesis. To explain these contradictory findings, Berger and Hannan (1997) argue that banks in more concentrated markets may take advantage of market power in pricing not for earning higher profits but to allow costs to rise as a consequence of slack management. Increased concentration, therefore, has a negative impact on bank efficiency. However, this explanation also implies a lack of market discipline created by market concentration. In addition, as pointed out by Jensen and Meckling (1976), the owner of a monopoly has the same incentive to monitor his managers than the owner of a competitive firm and therefore concentration *per se'* does not necessarily support slack management.

The "efficient structure hypothesis" (Demsetz, 1974) on the other hand, posits a reverse causality between competition and efficiency. According to the efficient structure hypothesis, more efficient firms have lower costs, which in turn lead to higher profits. Therefore, the most efficient firms are able to increase their market share, resulting in higher concentration. Firms may be exploiting greater x-efficiency (the so-called "efficiency hypothesis") or greater scale efficiency (the so-called "scale efficiency hypothesis"). If higher market concentration lowers competition, according to the efficiency hypothesis there should be an inverse relationship between competition and efficiency, thus reversing the causality running from efficiency to competition in the SCP paradigm. Berger (1995) finds some evidence that the efficiency hypothesis holds in US banking. In Europe, on the other hand, structural factors appear to be more important and the SCP hypothesis seems to hold (Goddard et al., 2001). However, the debate "collusion" versus "efficiency" has not yet been satisfactorily resolved (Goddard et al., 2007).

The New Empirical Industrial Organisation (NEIO) literature, on the other hand, argues that factors other than market structure and concentration may affect competitive behaviour, such as entry/exit barriers and the general contestability of the market (Baumol et al. 1982; Bresnahan, 1989; Rosse and Panzar, 1977; Panzar and Rosse, 1987). In the so-called non-structural approaches it is not assumed a priori that concentrated markets are not competitive because contestability may depend on the extent of potential competition and not necessarily on market structure. Another advantage of non-structural models is that there is no need to specify a geographic market, since the behaviour of individual banks gives an indication of their market power. Non-structural measures of competition are mainly based on the Lerner (1934) measure of monopoly power. Specifically, they include measures of competition between oligopolists (Iwata, 1974) and those that test for the competitive conditions in contestable markets (Bresnahan, 1982; Lau, 1982; Panzar and Rosse, 1987). Several recent empirical applications point to the need of a structural contestability approach when studying the degree of competitiveness in the banking industry (see Claessens and Laeven, 2004) as concentration is a poor proxy for competition. Relatively new research warns that bank size and types may affect competitiveness differently and that using only one measure may not be sufficient for inferring on the true degree of competition (Berger et al., 2004).

The literature relating the concepts of concentration, competition and efficiency usually refers to inefficiency as costs deriving from slack management. This corresponds well to the concept of x-efficiency, which involves avoiding waste by achieving the maximum possible output from a given set of inputs or by minimising the inputs given an achievable set of outputs. There is a vast literature on the measurement of cost structure and efficiency in banking and on the determinants of efficiency (see the reviews by Berger and Humphrey, 1997 and Goddard et al., 2001). Efficiency is commonly estimated by employing parametric methods (such as Stochastic Frontier Analysis, SFA) or non-parametric methods, the most popular of which is Data Envelopment Analysis (DEA). The early bank efficiency literature shows that before deregulation EU banking markets were often characterised by the presence of many institutions operating at a non-optimal scale with relatively high excess capacity. Inefficient banks could survive mainly because of the lack of competitive pressures and the fact that, in some cases, the domestic authorities, while acting as protectors of their banking sectors, were keen on maintaining a large number of banks in their systems. With deregulation and higher competition, EU bank efficiency improved as banks were under pressure to cut costs (see, among others, Amel et al., 2004 and Casu et al., 2004). The process of concentration also accelerated so that banks could operate at a better (and more efficient) scale. As a result, the correlation between competition and efficiency should be positive, although higher concentration levels in the banking sector could subsequently limit the welfare gains through the loss in competition.

Only a handful of studies directly address the issue of the relationship between the intensity of competition and efficiency. It was commonly expected that increased competition would in turn foster efficiency by providing incentives to managers to cut costs in order to remain profitable. Recent research has however indicated that the relationship between competition and banking system performance is more complex and that the view that competition is unambiguously good is more naïve in banking than in other industries (Claessen and Leaven, 2004). The empirical evidence on the links between concentration and banking sector efficiency does not suggest an unambiguously positive – or negative – relationship (Demirgüç-Kunt and Levine, 2000). Furthermore, there are conflicting results on the impact of increased bank concentration – through M&As – on efficiency, deposit rates and bank profitability (Berger and Humphrey, 1992; Pilloff, 1996). Based on European banking data, Casu and Girardone (2006) and Weill (2005) find an inverse relationship between competition and efficiency. They find little evidence that banking system concentration negatively relates to competitiveness but suggest that the most efficient banking systems are also the least competitive. It may be the case that larger size banks have been able to cut cost, exploit both economies of scale and x-efficiencies, and achieve a degree of market power in their local markets, therefore increasing both prices and profits. This may indicate that that the pro-competitive deregulation of the EU banking markets might have led to increased market power for the most efficient banks, therefore lowering the pressures initially resulting from increased competition.

This study contributes to the literature both by extending the analysis of the relationship between bank competition, concentration and efficiency to a cross-section of countries and by testing the direction of the causal relationship between competition and efficiency. In a bi-variate framework, the first variable is said to cause the second variable in the Granger sense if the forecast for the second variable improves when lagged values for the first variable are taken into account (Granger, 1969). Though originally designed for pairs of lengthy time series, Granger tests are increasingly used to evaluate causal relationships in panel data. The extension of the original Granger methodology to panel data has the potential to improve upon the conventional Granger analysis for all of the reasons that panel analysis is generally preferable to cross-sectional or traditional time series analysis (see Greene, 2003). The introduction of a panel data dimension permits the use of both cross-sectional and time-series information to test any causality relationships between two variables. In this paper, we employ dynamic panel data methods; specifically we use the 'difference' and 'system' (or 'combined') Generalised Method of Moments (GMM) procedures developed by Holtz-Eakin et al. (1988), Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998). Our findings suggest that in the majority of cases the Granger coefficient is negative, thereby indicating that cost efficiency negatively Granger-causes competition (i.e. an increase in bank efficiency Granger-causes a decrease in competition). On the other hand, the causality running from competition to efficiency, although positive, is relatively weak. These results pose additional questions for competition policies. Regulatory initiatives aimed at further enhancing competition in EU banking should be aware of its possible adverse effects on efficiency. Decreases in bank efficiency can either be a signal that banks are struggling under excessive competition, with serious implications for the sector stability, or that they are reacting to competition by consolidating and therefore increasing market power.

3. Methodology and Data

3.1 NEIO Measures of Competition: the Lerner Index of monopoly power

The Lerner Index of monopoly power is a non-structural indicator of the degree of market competition that were developed in the context of the NEIO (e.g. Iwata, 1974; Baumol et al. 1982; Bresnahan, 1989; Rosse and Panzar, 1977; Panzar and Rosse, 1987).

The Lerner index of monopoly power measures the mark-up of bank output prices over the marginal cost of production and can be approximated empirically using the translog functional form with three inputs and a single output:[1]

$$\begin{aligned} \ln TC_{it} &= \alpha_0 + \alpha_1 \ln Q_{it} + \sum_{j=1}^{3} \beta_j \ln P_j + \frac{1}{2}[\delta_{it} \ln Q_{it}{}^2 + \sum_{j=1}^{3}\sum_{i=1}^{3} \gamma_{ij} \ln P_j \ln P_i] + \\ &+ \sum_{j=1}^{3} \rho_j \ln Q_{it} \ln P_j + t_1 T + \frac{1}{2} t_{11} T^2 + \theta_t T \ln Q_{it} + \sum_{j=1}^{3} \psi_{tj} T \ln P_j + \varepsilon_{it} \end{aligned} \qquad (1)$$

[1] For the theoretical derivation of the Lerner index, see e.g. Fernandez de Guevara et al. (2005).

where TC is total costs; Q is total assets; P_1 is the price of labour; P_2 is the price of deposits and P_3 is the price of capital; T is a time trend; α, β, δ, γ, ρ, t, θ, ψ are parameters to be estimated; and ε is the error term.[2] The cost function is estimated using a common frontier and allows the derivation of marginal costs (MC) as follows:

$$MC_{it} = \frac{TC_{it}}{Q_{it}}\left(\alpha_1 + \delta \ln Q_{it} + \rho_j \ln Q_{it} + \theta_t T \ln Q_{it} + \varepsilon_{it}\right) \tag{2}$$

Marginal costs derived from equation (2) are used to calculate the Lerner index:

$$LERNER = \frac{p_i - MC_{it}}{p_i} \tag{3}$$

where p_i the price of production output Q total assets and is calculated as total revenue (interest plus non-interest income) divided by total assets. LERNER=0 it indicates perfect competition, while LERNER=1 indicates monopoly.

3.2 Frontier Efficiency Analysis

The literature on the measurement of efficiency frontiers can be divided in two main streams: parametric techniques, such as the Stochastic Frontier Analysis (SFA) and non-parametric techniques such as Data Envelopment Analysis (DEA).

The standard SFA generates estimates of X-efficiencies for each banking institution along the lines first suggested by Aigner et al. (1977). Specifically, X-efficiency scores are estimated using the Battese and Coelli's (1992) time-varying stochastic frontier approach for panel data with firm effects which are assumed to be distributed as truncated normal random variables and are also permitted to vary systematically with time (see also Battese and Coelli, 1993; and Coelli et al., 1998). The chosen functional form for the cost function is the translog as specified in equation (1) above with the same three inputs, but with two outputs (total loans and total securities) and a time trend. The final specification is as follows:

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[2] We apply the common restrictions of standard symmetry and homogeneity in prices to the translog functional form.

$$\ln TC_{it} = \alpha_0 + \sum_{i=1}^{2} \alpha_1 \ln Q_i + \sum_{j=1}^{3} \beta_j \ln P_j + \frac{1}{2}[\sum_{i=1}^{2}\sum_{j=1}^{3} \delta_{ij} \ln Q_i \ln Q_j + \sum_{j=1}^{3}\sum_{i=1}^{3} \gamma_{ij} \ln P_j \ln P_i] + \\ + \sum_{i=1}^{2}\sum_{j=1}^{3} \rho_{ij} \ln Q_i \ln P_j + t_1 T + \frac{1}{2} t_{11} T^2 + \sum_{i=1}^{2} \theta_{ti} T \ln Q_i + \sum_{j=1}^{3} \psi_{tj} T \ln P_j + \varepsilon_{it} \quad (4)$$

The single-equation stochastic cost model is represented by $\ln TC_{it} = \ln TC^*(Q_{it}, P_{jt}; B) + \varepsilon_{it}$ where the variables are defined as above (equation 1, Section 3.1) and B is a vector of unknown parameters to be estimated. Finally ε_{it} is a two-components error term that for the i-th firm that can be written as follows: $\varepsilon_{it} = u_{it} + v_{it}$ where v_{it} is a two-sided error term capturing the effects of statistical noise, assumed to be independently and identically normal distributed with zero mean and variance σ_v^2 and independent of the $u_{it} = \{u_i \exp[-n(t-T)]\}$ where u_i is a one-sided error term capturing the effects of inefficiency and assumed to be half normally distributed with mean zero and variance σ_u^2; n is an unknown parameter to be estimated capturing the effect of inefficiency change over time.

On the other hand, DEA is a mathematical linear programming technique developed by Charnes, Cooper and Rhodes in 1978 (CCR) which identifies the efficient frontier from the linear combination of those units/observations that (in a production space) use comparatively less inputs to produce comparatively more outputs. In particular, if N firms use a vector of inputs to produce a vector of outputs, the input-oriented CCR measure of efficiency of a particular firm is calculated as:

$$\begin{aligned} &\min_{\theta,\lambda} \theta_i \\ &s.t. \quad \sum_{r=1}^{N} y^t{}_{mr} \lambda^t{}_r \geq y^t{}_{mi} \\ &\qquad \sum_{r=1}^{N} x^t{}_{kr} \lambda^t{}_r \leq \theta_i x^t{}_{ki} \\ &\qquad \lambda^t{}_r \geq 0 \end{aligned} \quad (5)$$

where $\theta_i \leq 1$ is the scalar efficiency score for the i-th unit. If θ_i =1 the i-th firm is efficient as it lies on the frontier, whereas if θ_i < 1 the firm is inefficient and needs a (1-θ_i) reduction in the inputs levels to reach the frontier.

The CCR model assumes constant returns to scale (CRS), which is the optimal scale in the long-run. The additional convexity constraint $\sum \lambda_i = 1$ can be included in (5) to allow for variable returns to scale (VRS) (see Banker, Charnes and Cooper (1984) or BCC model The BCC model is used in this paper since several factors such as imperfect competition and regulatory requirements may cause a unit not to be operating at the optimal scale.[3]

Choosing the appropriate definition of bank output is a relevant issue for research into banks' cost efficiency. The approach to output definition used in this study is a variation of the *intermediation approach*, which was originally developed by Sealey and Lindley (1977) and posits that total loans and securities are outputs, whereas deposits along with labour and physical capital are inputs. Specifically, the input variable used in this study is Total Costs (Personnel Expenses + Other Administrative Expenses + Interest Paid + Non-Interest Expenses) whereas the output variables capture both the traditional lending activity of banks (total loans) and the growing non-lending activities (other earning assets).

3.3 Dynamic Panel Data Granger-Type Causality estimation

Granger testing is a common method of investigating causal relationships (Granger, 1969) by estimating an equation in which y is regressed on lagged values of y and the lagged values of an additional variable x. The null hypothesis is that x does not Granger-cause y. If one or more of the lagged values of x is significant, we are able to reject the null hypothesis and we can conclude that x Granger causes y. Though imperfect, it is a standard and useful tool for evaluating the character of the causal relationship between two variables. The test was originally designed for pairs of lengthy time series; however, econometricians have recently begun to modify Granger tests to incorporate panel dynamics (see for example Arellano and Bond 1991; Holtz-Eakin et al. 1988; Hurlin 2005; and Hurlin and Venet 2001).

In this study, in order to statistically test the Granger causality between efficiency and competition we employ dynamic panel data methods. Specifically we use the 'difference' and 'system' (or 'combined') Generalised Method of Moments (GMM) procedures developed by Holtz-Eakin et al. (1988), Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998).

[3] For an introduction to DEA methodology see, among others, Coelli et al. (1998); Thanassoulis (2001); see Thanassoulis (2007) for an extensive review of this literature.

These methods are useful for panels characterised by a relatively low number of years and a large number of cross-sections per year (Roodman, 2006) and they help deal with possible problems of endogeneity and measurement error (see in the growth literature e.g. Bond et al., 2001).[4]

The single equation to be estimated is an autoregressive-distributed linear specification as follows:

$$y_{it} = \alpha_0 + \sum_{j=1}^{n} \alpha_j y_{i(t-j)} + \sum_{j=1}^{n} \beta_j x_{i(t-j)} + \theta_t + \eta_i + \upsilon_{it} \tag{6}$$

where y_{it} is the dependent variable, α_0 is the intercept, $y_{i(t-j)}$ is jth lag of the dependent variable, $x_{i(t-j)}$ is jth lag of an explanatory variable of interest, α_j and β_j are parameters to be estimated, θ_t is a common time effect, η_i is an individual bank specific effect, and υ_{it} is a disturbance term. To avoid cross-sectional dependence, the disturbances are assumed to be orthogonal to each other. Specifically, the following AR(2) model has been used in this application:

$$y_{it} = \alpha_0 + \alpha_1 y_{i,t-1} + \alpha_2 y_{i,t-2} + \beta_1 x_{i,t-1} + \beta_2 x_{i,t-2} + \theta_t + \eta_i + \upsilon_{it} \tag{7}$$

The estimation of an AR(2) model allows us to test the Granger causality joint hypothesis of $\beta_2 = \beta_1 = 0$. Since we expect causality to run in either direction, y_{it} and x_{it} are represented alternatively by a measure of competition (the Lerner Index of monopoly power) and a measure of bank cost efficiency (estimated using parametric and non-parametric methods). This will allow us to investigate in a six-year dataset for five EU countries whether changes in competition patterns precede (Granger-cause) changes in bank efficiency, and/or vice-versa whether changes in efficiency Granger-cause changes in competition.

We first run pooled OLS and fixed and random effects regressions. The limitations of these models when estimating equations similar to (6) above are well described in e.g. Bond (2002) and Roodman (2006). We then employ the so-called "difference" GMM (DIF-GMM) estimator developed by Arellano and Bond (1991) for the coefficients in equation (7) where the lagged levels

[4] Recent banking studies (e.g. Berger and DeYoung, 1997, and Williams, 2004) use standard OLS techniques to test the Granger causality between estimated bank efficiency levels, problem loans and capitalisation. While our method should be more reliable than using standard OLS, the generated regressors problem may still affect our results that should then be interpreted with care.

of the regressors are instruments for the equation in first differences. The so-called "difference" GMM (DIF-GMM) estimator relies upon the following moment conditions:[5]

$$E\left(y_{it-s}\Delta\upsilon_{it}\right)=0 \quad \text{for } s\geq 2; t=4,...,T \tag{8}$$
$$E\left(x_{it-s}\Delta\upsilon_{it}\right)=0 \quad \text{for } s\geq 2; t=4,...,T$$

The Arellano and Bond's (1991) DIF-GMM procedure assumes a set of strict restrictions for the model to be valid: serial correlation in the first order errors and no second-order GMM residual serial correlation. Moreover, it recommends the Sargan statistics of overidentifying restrictions (also known as Hansen's J) to tests the validity of the instrumental variables.

Following Arellano and Bover (1995) and Blundell and Bond (1998) we also employ the system GMM (SYS-GMM) estimator that was designed to overcome some of the limitations of the DIF-GMM.[6] The method involves the estimation of a system composed of equations in first differences and equations in levels where the additional internal instruments are both lagged levels and differences of the series (Blundell and Bond, 1998). In order to consider the additional moments as valid instruments for equation (7), the following additional moment conditions must be satisfied:

$$E\left(\Delta y_{it-2}\Delta\upsilon_{it}\right)=0 \quad \text{for } t=4,...,T \tag{9}$$
$$E\left(\Delta x_{it-2}\Delta\upsilon_{it}\right)=0 \quad \text{for } t=4,...,T$$

With the AR(2) model described in equation (7), a Granger causality test can be measured with a joint test of the two lags of efficiency and competition and is distributed as χ^2 with two degrees of freedom. The null hypothesis is that the sum of the lagged coefficients is zero: if the probability is less than 0.10 then the null hypothesis that *x* Granger cause *y* is not rejected at the 10% significance level. The sign of the causal relationship is determined by the sum of the jointly significant

[5] Arellano and Bond (1991) derive the moment conditions for AR(1) and AR(2) models and recommend using all the available lags dated *t*-2 and earlier in order to obtain an efficient GMM estimator.

[6] For example, where the series are highly persistent the lagged levels may be weak instruments for first differences (see e.g. Bond, 2002).

coefficients. A positive (negative) sum implies that the causal relationship is also positive (negative), that is an increase (decrease) in x in the past increased (decreased) the y in the present.[7]

Moreover we use an incremental Sargan/Hansen test for the validity of the additional moment restrictions described in (6) required by the SYS-GMM as follows: if S is the Sargan statistics obtained under stronger assumptions and S' is the Sargan statistics obtained under weaker assumptions, then the difference $S - S'$, is asymptotically distributed as χ^2.

Finally the estimated models are also subjected to a test that measures the stability over time (or 'long-run effect') of the x over the y. The extant literature suggests the use of a test of the restriction $\beta_1 + \beta_2 = 0$ that should be interpreted as follows: a rejection of the restriction implies that there is evidence for a long-run effect of x on y. Else, y will depend on the change in x rather than on his level.[8]

3.4 Data

The data on EU commercial banks are derived from BankScope, a global database published by Bureau Van Dijk. The data are collected for an unbalanced sample of 2,701 commercial bank observations operating in France, Germany, Italy, Spain and the United Kingdom between 2000 and 2005. We restricted the investigation to commercial banks as there are still significant differences in the retail market structure among countries and in some countries the saving banking sector is still partially benefiting from state help[9]. The choice of an unbalanced panel is justified mainly to account for mergers and acquisitions, entry and exit during the period. We use data from consolidated accounts, where available, to avoid double-counting. As a result, the banking market for country X is the defined as the hypothetical market where banks from country X operate and not the national borders of a country (see Bikker and Haaf, 2002). The data were analysed for inconsistencies, reporting errors, missing values and outliers. The final sample is shown in Table 1,

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[7] While the Granger causality test is a useful tool to denote whether a variable is correlated with the lagged values of the other – after controlling for its own lags, some caution should be used in interpreting the results. Among the main limitations of the Granger are that it is contingent on the choice of variables included in the equations and the number of lags. Moreover, if the sample is unbalanced (as in our case) by increasing the number of lags, the number of observations will be reduced significantly and this may affect the consistency of the results.

[8] For more details on this test see Bond and Windmeijer (2005).

[9] For example, until 2005 the German Landesbanks benefited state guarantees have secured the high ratings and have given them access to cheap funding.

which lists the total and average number of banks in the sample by country and year as well as the total average assets over the period.

<Insert Table 1 around here>

It is interesting to note that Italian commercial banks have an average size that is roughly half that of the French, German and Spanish ones. Moreover, UK commercial banks have an average size of almost five times that of Italian banks. The number of banks in the sample is decreasing over time (with the exception of Italy) as the banking sector consolidates further.

4. Empirical results

4.1 Competition Patterns in European Banking

Table 2 shows the means of the structural indicators of market concentration across our sample of EU countries over the period 2000-2005. The Herfindahl-Hirshman Index (HH) represents the market share (in terms of total assets, total loans and total deposits) of every firm in the market whereas the CR-5 indicates the market share of the five largest firms in the market. We also calculated the HH for the sub-sample of commercial banks on Total Loans, Total Deposits as well as Total Assets.

The data show that national conditions still vary considerably across countries and this is reflected in the different market structures of the retail banking industry in general and of the commercial banking industry in particular. Against the EU average (in 2005, HH was 601 and CR-5 was 43% for the EU-25), concentration levels remain relatively low in Germany, Italy and the UK. Most countries, however, show an increase in concentration during the period of analysis. In the UK alone, in the six years period from 2000 concentration (measured as the market share of the five largest banks) increased by 28.57%. Looking at the separate information for commercial banks, they seem to operate in more concentrated markets and this might be also reflected in their measure for market power.

<Insert Table 2 around here>

Figure 1 shows the evolution of marginal costs and of the Lerner index of monopoly power over the sample period and country differences are also apparent. The banking sector in the UK and

Germany seem to enjoy the highest relative margin and Spain the lowest. These results are broadly in line with those of Fernandez de Guevara and Maudos (2005).

<Insert Figure 1 around here>

Marginal costs decreased in all countries (with the exception of France) over the sample period, showing an increase in 2005. Italy and Spain, which display the highest average marginal costs, also display the biggest decrease, possibly because of the reduction of both financial costs and operating costs. Despite the decrease in marginal costs, Italy and Spain also display the highest increase in the Lerner Index, thus indicating that the decrease in marginal cost was smaller than the increase in the average price of assets. On the other hand, the Lerner Index decreases over the period in France and in the UK. Comparing our results with averages for the whole banking system (see Fernandez de Guevara and Maudos, 2005), they confirm that, despite being more concentrated, commercial banks enjoy a lower market power compared to saving banks. This reinforces our decision to concentrate this analysis on the commercial banking sector because of the potential distortions still existing in the EU saving banking sector.

4. The evolution of bank efficiency: SFA and DEA analysis

The yearly SFA and DEA results for the countries in our sample, as well as the average efficiency over the period are shown in Table 3.

The average overall efficiency score for the five EU banking industries over the whole sample period is 75.43% for SFA and 71.23% for DEA, thus indicating a 24.57% and 28.77% respectively average potential reduction in inputs utilisation. The results for the different EU countries in 2005 vary between 74.51% in Germany and 62.04% in Italy in the DEA estimations and between 80.47% in Italy and 68.88% in Spain for the SFA estimations.

<Insert Table 3 around here>

Both methodologies indicate and average inefficiency scores of about 30%, a result that is broadly in line with the main literature on bank efficiency (see Goddard et al., 2007). Differently from most studies analysing bank efficiency during the 1990s, which find improvements in resources utilisation, the yearly results seem to indicate, for most countries, an increase in input wastage from 2000-2001 onwards resulting in lower average inefficiencies (see Figure 2)[10]. This trend could be explained by the initial effort towards cutting costs fostered by deregulation and increased competition; the wave of mergers and acquisitions that followed might have imposed higher costs on banks, thereby decreasing their cost efficiency. However, decreases in bank efficiency can also be a signal that banks are struggling under excessive competition, with serious implications for the sector stability, or that they are exploiting increased market power.

<Insert Figure 2 around here>

The analysis so far has highlighted that the main EU banking markets are becoming progressively more concentrated and less efficient. Furthermore, different measures of competition do not exclusively indicate an overall increase of competitive pressure over the period.

The next section will investigate the relationship between efficiency and competition; particularly we study the direction of the causal relationship (if any) between the two variables.

4.2 The Relationship and Causality between Competition and Efficiency

Tables 4 and 5 report the results of our empirical analysis on the relationship and causality between competition and efficiency. These are derived from the estimation of cross-sectional pooled OLS regression models, fixed and random effects panels, the DIF-GMM robust estimators and the two-step robust SYS-GMM model. Our specifications include two lags of the dependent and explanatory variables and they are carried out twice using as alternative measures of cost efficiency the parametric SFA and the non-parametric DEA (results are reported in panels (a) and (b) respectively).

<Insert Table 4 around here>

In the first set of estimations we test the causality from efficiency to competition (Table 4). Competition, measured as the Lerner index of monopoly power, is estimated as a function of lagged competition and lagged cost efficiency. Looking at the results, the first and second lags of competition are usually significantly different from zero at the one per cent level in both panels (a) and (b). This indicates that competition at time *t* is influenced by previous years' competition. Granger causality is assessed as the joint test of the two lags of efficiency on competition as

[10] Given the use of an unbalanced panel to account for entry and exit and M&As, it is not possible in a DEA framework to compare directly the yearly results as the observations composing the sample might differ from year to year. It is however possible to note the decreasing average yearly results, which are consistent with the econometric estimations.

follows: $\beta_1 = \beta_2 = 0$. A p-value <0.10 rejects at the 10% significance level the null hypothesis that efficiency does not Granger-cause competition. However, following Arellano and Bond (1991), three additional conditions should be satisfied for the Granger causality to be statistically valid: a significant AR(1) serial correlation, lack of AR(2) serial correlation and a high Sargan/Hansen test statistics: a low p-value (<0.10) for this statistics indicates that the model is mispecified. Our findings in Table 4 suggest that in the majority of cases the Granger coefficient is negative, thereby indicating that cost efficiency negatively Granger-causes competition (i.e. an increase in bank efficiency Granger-causes a decrease in competition). The Granger coefficient is significant and the three additional conditions above are satisfied in at least three cases, particularly when lagged SFA efficiency measures are included as explanatory variables. The Granger causality test rejects the null of non-causality in the case of OLS estimation, random effects and two-step robust GMM estimators. Finally the long-run effect is significant only in one case in panel (b) therefore it is not possible to infer on the stability of the relationship between competition and efficiency over the long period.

Table 5 shows the results for the causality running from competition to efficiency. The significance of the coefficients for the first and second lags of efficiency seem to suggest that efficiency is affected significantly by previous years' efficiency (and in some cases the inefficiency as noted by the negative and significant sign of the second lag in panel a). Overall, the results seem to suggest that the Granger causality running from competition to efficiency is relatively weak. However, where significant, the sign of the Granger coefficient is positive.

<Insert Table 5 around here>

Overall, our results seem to provide some empirical evidence to support the existence of a cost efficiency-to-competition negative causation for our sample of European commercial banks. In other words, higher cost efficiency seems to cause a decrease in competition. This is consistent with the hypothesis that more efficient banks are in a position to exploit market power and therefore there seem to be a trade-off between efficiency and competition. On the other hand it seems that the effect of competition on efficiency is less clear. These results seem to be consistent with the "*efficient structure hypothesis*" whereby the best managed firms have the lowest costs and the largest market shares, which in turns leads to a higher degree of concentration. It seems therefore that efficiency determines competition, with a negative causality, whereas competition might stimulate managers to become more efficient, but the causality, although positive, is weak.

5. Conclusions

Competition is generally considered as a positive force, often associated with increased efficiency and enhanced consumers' welfare. However, in the banking sector it is a more controversial issue. The acceleration in the recent consolidation process is raising concerns about increased concentration in the banking sector and its potential implications for public policy deriving from increased market power in the banking sector. Policymakers are faced with the contrasting issues as to whether competitive forces are positively impacting on bank performance and efficiency or whether the consolidation wave poses a threat to competition in the sector. Using bank level balance sheet data for the major EU commercial banking markets, this paper aims to shed some light on these issues by investigating the relationship between alternative measures of competition, concentration and bank-specific efficiency levels. The dynamics of the relationship between competition and efficiency are tested by using a dynamic panel data Granger causality test. Our findings suggest a negative causation between efficiency and competition, whereas the causality running from competition to efficiency, although positive, is relatively weak. These results pose further questions for competition policies. Recent decreases in bank efficiency could either be a signal that banks are struggling under excessive competition, with serious implications for the sector stability, or that they are exploiting increased market power. The latter might seem a more likely explanation. However, as Vives (2001) pointed out, market power could be beneficial in banking as it provides incentives for banks to undertake less risky strategies.

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Table 1
Total Average Size of Sampled Banks and Number of Institutions

	France	Germany	Italy	Spain	UK	Total by year
2000	101	111	121	52	76	461
2001	105	107	130	56	70	468
2002	99	104	125	52	72	452
2003	93	104	144	47	78	466
2004	86	96	142	46	77	447
2005	77	89	135	39	67	407
Total number of banks	561	611	797	292	440	2,701
Total assets by country over the period (mil €)	22,708.0	24,657.5	11,690.6	22,938.6	49,947.2	

Table 2
Concentration Measures: Herfindahl-Hischman Index (HH) and CR-5

	2000	2001	2002	2003	2004	2005	2000-2005
HH Total Loans (Commercial banks)							
France	1373	1443	1282	1271	849	1371	-0.14%
Germany	1928	1956	1764	1635	2164	2010	4.27%
Italy	987	872	945	646	564	1137	15.22%
Spain	1890	2112	1606	2650	2309	3064	62.15%
UK	924	917	1027	1085	1122	1084	17.29%
HH Total Deposits (Commercial Banks)							
France	1374	1704	1427	1470	1417	1682	22.42%
Germany	1872	1827	1774	1953	2781	2826	50.97%
Italy	1138	992	974	742	730	1439	26.50%
Spain	2016	2321	1713	2870	2328	3326	64.95%
UK	935	955	1066	1116	1131	1327	41.88%
HH Total Assets (Commercial Banks)							
France	1511	1957	1603	1669	1386	1622	7.34%
Germany	1944	1933	1814	2019	2776	2833	45.72%
Italy	1038	915	977	707	675	1315	26.71%
Spain	2096	2466	1824	2992	2481	3459	65.02%
UK	940	952	1080	1139	1164	1293	37.65%
HH Total Assets (Banking Sector)							
France	587	606	551	597	623	758	29.13%
Germany	151	158	163	173	178	174	15.23%
Italy	190	260	270	240	230	230	21.05%
Spain	581	532	513	506	482	487	-16.18%
UK	264	282	307	347	376	399	51.14%
CR-5 (Banking Sector)							
France	47	47	45	47	50	53	12.77%
Germany	20	20	21	22	22	22	10.00%
Italy	23	29	31	28	26	27	17.39%
Spain	46	44	44	43	42	42	-8.70%
UK	28	29	30	33	35	36	28.57%

Source: Authors' calculations and ECB (2006).

Table 3
DEA and SFA Efficiency Scores by Year and Country

	Countries	2000	2001	2002	2003	2004	2005	2000- 2005
DEA Efficiency Scores	France	69.46	67.29	65.59	65.57	3.69	62.39	-10.17%
	Germany	72.29	73.33	69.45	68.73	70.50	74.51	3.07%
	Italy	76.33	83.71	65.31	63.81	77.49	62.04	-18.72%
	Spain	84.67	80.11	79.47	72.20	7520	78.64	-7.13%
	UK	72.12	76.28	62.78	69.62	66.71	67.63	-6.23%
	Average	*74.97*	*76.14*	*68.52*	*67.98*	*70.12*	*69.04*	*-7.91%*
SFA Efficiency Scores	France	74.10	73.83	71.17	71.86	70.23	69.75	-5.87%
	Germany	74.77	74.13	73.76	72.09	71.34	70.85	-5.25%
	Italy	84.13	83.35	81.42	81.17	80.57	80.47	-4.35%
	Spain	75.19	73.32	71.77	72.20	71.51	68.88	-8.40%
	UK	76.95	75.46	74.15	73.48	72.53	70.54	-8.33%
	Average	*77.03*	*76.02*	*74.45*	*74.16*	*73.23*	*72.10*	*-6.40%*

Table 4
Does Cost Efficiency Granger-Cause Competition?

Dependent variable *y*= LERNER INDEX	Variables and tests	OLS levels	Fixed Effects	Random Effects	DIF-GMM t-2 Robust	Two-step SYS-GMM Robust
(a) *x* = SFA cost efficiency	LER1	.8832*** (.0339)	.2027*** (.0283)	.7658*** (.0232)	.4651*** (.2002)	.7217*** (.1437)
	LER2	.0602* (.0324)	-.0940*** (.0279)	.1163*** (.0225)	.0037 (.0488)	.1233 (.1397)
	SFAEFF1	.0003 (.0004)	-.0016 (.0058)	.0002 (.0006)	-.0081 (.0067)	.0002 (.0005)
	SFAEFF2	-.0003 (.0004)	.0014 (.0059)	-.0002 (.0007)	.0079 (.0068)	-.0002 (.0005)
	m1 p-value	.3485	n/a	n/a	.046	.085
	m2 p-value	n/a	n/a	n/a	.956	.727
	Sargan/Hansen p-value	n/a	n/a	n/a	.300	.577
	Granger coefficient	-.0000	-.0002	-.000	-.00012	-.0000
	Granger causality p-value	.5537	.0519*	.9299	.0916*	.9197
	Difference Sargan/Hansen					0.99
	Test of $\beta_1 + \beta_2 = 0$ p-value	.393	.113	.717	.346	.800
(b) *x*= DEA cost efficiency	LER1	.8839*** (.040)	.2058*** (.0282)	.7684*** (.0232)	.5722** (.2353)	.5758*** (.2782)
	LER2	.0588** (.0325)	-.1038*** (.0279)	.1147*** (.0225)	-.00099 (.0494)	.2940 (.2712)
	DEAEFF1	-.0004 (.0004)	.00023 (.0004)	-.00041 (.0004)	.00142 (.0016)	.00034 (.0005)
	DEAEFF2	.0002 (.0004)	.0006*** (.0004)	.0002 (.0004)	.00094 (.0007)	.0004 (.0005)
	m1 p-value	.334	n/a	n/a	.045	.477
	m2 p-value	n/a	n/a	n/a	.956	.413
	Sargan/Hansen p-value	n/a	n/a	n/a	.201	.853
	Granger coefficient	-.00019	.0009	-.0002	.0024	.0007
	Granger causality p-value	.4341	.203	.493	.4032	.632
	Difference Sargan/Hansen					0.599
	Test of $\beta_1 + \beta_2 = 0$ p-value	.324	.116	.472	.27	.342

Note: Year dummies are included in all models. OLS= Ordinary Least Squares; DIF-GMM= difference GMM. SYS-GMM = system GMM. SFAEFF= cost efficiency estimated using SFA. DEAEFF= cost efficiency estimated using DEA. *,**,*** indicates significance at the 10%, 5% and 1% levels. Asymptotic standard error in parentheses. Huber-White standard errors are computed for one-step estimates while the two-step estimates are Windmeijeier corrected. m1 and m2 are tests for first-order and second-order serial correlation. Sargan/Hansen is a test of the over-identifying restrictions for the GMM estimators. All computations done using Stata.

Table 5
Does Competition Granger-Cause Cost Efficiency?

Dependent variable *y*: COST EFFICIENCY	Variables and tests	OLS levels	Fixed Effects	Random Effects	DIF-GMM t-2 Robust	Two-step SYS-GMM Robust
(a) *x* = SFA cost efficiency	SFAEFF1	2.088*** (.0022)	2.0764*** (.0004)	2.0837*** (.0003)	2.0738*** (.0019)	2.0875*** (.0036)
	SFAEFF2	-1.090*** (.0023)	-1.079*** (.0004)	-1.0858 *** (.0004)	-1.0759*** (.0019)	-1.0897*** (.0037)
	LER1	.01280 (.0093)	-.0008 (.0019)	-.0021 (.0024)	.0008 (.0151)	.0006 (.0048)
	LER2	-.0141 (.0100)	.0066*** (.0019)	.0034 (.0024)	.0049*** (.0028)	-.0066*** (.0036)
	Serial correlation (AR1) p-value	.0000	n/a	n/a	.000	.001
	Serial Correlation (AR2) p-value	n/a	n/a	n/a	.000	.002
	Sargan/Hansen p-value	n/a	n/a	n/a	.449	.841
	Granger coefficient	-.0013	.0058	.0013	.0057	-.0059
	Granger causality p-value	.2206	.0017**	.330	.1998	.1565
	Difference Sargan/Hansen					0.163
	Test of $\beta_1 + \beta_2 = 0$ p-value	.911	.011	.660	.722	.205
(b) *x* = DEA cost efficiency	DEAEFF1	.6711*** (.0378)	.0456*** (.0381)	.6017*** (.028)	.5400*** (.2026)	.7783** (.4121)
	DEAEFF2	.1721*** (.0376)	-.1146 (.0348)	.1855*** (.028)	.0944 (.0707)	.4717 (.4275)
	LER1	3.9751 (2.5051)	4.4103* (2.5743)	4.221** (1.8137)	-36.8735 (31.7019)	2.3988 (2.7498)
	LER2	.0295 (2.6762)	-.1967 (2.5451)	-.1512 (1.7705)	-6.5340 (5.2405)	2.2130 (3.6485)
	Serial correlation (AR1) p-value	.497	n/a	n/a	.003	.590
	Serial Correlation (AR2) p-value	n/a	n/a	n/a	.151	.401
	Sargan/Hansen p-value	n/a	n/a	n/a	.000	.201
	Granger coefficient	4.005***	4.2136	4.070***	-43.4075	4.6118
	Granger causality p-value	.001	.2143	.001	.4060	.4521
	Difference Sargan/Hansen					0.011
	Test of $\beta_1 + \beta_2 = 0$ p-value	.000	.1750	.000	.217	.232

Note: Year dummies are included in all models. OLS= Ordinary Least Squares; DIF-GMM= difference GMM. SYS-GMM = system GMM. SFAEFF= cost efficiency estimated using SFA. DEAEFF= cost efficiency estimated using DEA. *,**,*** indicates significance at the 10%, 5% and 1% levels. Asymptotic standard error in parentheses. Huber-White standard errors are computed for one-step estimates while the two-step estimates are Windmeijeier corrected. m1 and m2 are tests for first-order and second-order serial correlation. Sargan/Hansen is a test of the over-identifying restrictions for the GMM estimators. All computations done using Stata.

Figure 1
Marginal Cost and Lerner Index of Monopoly Power

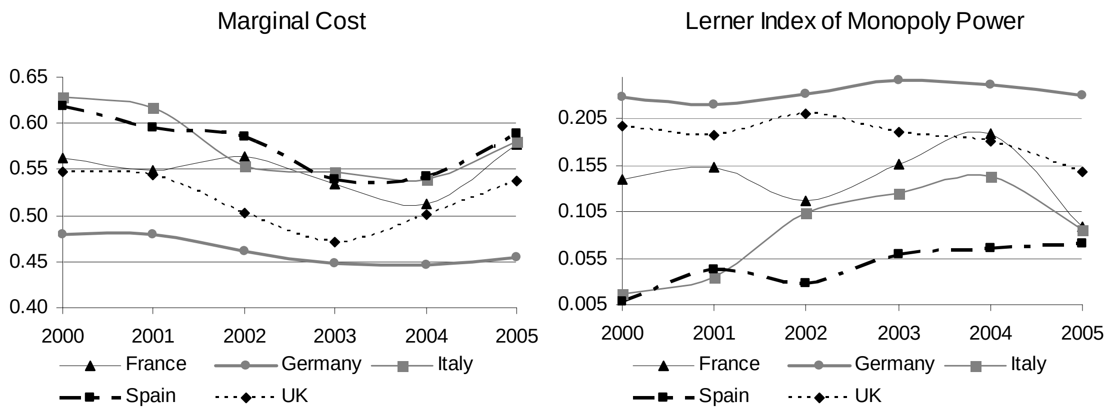

Figure 2
DEA and SFA Yearly Averages