The joint estimation of bank-level market power and efficiency

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Abstract

The aim of this study is to provide a methodology for the joint estimation of efficiency and market power of individual banks. The proposed method utilizes the separate implications of the new empirical industrial organization and the stochastic frontier literatures and suggests identification using the local maximum likelihood (LML) technique. Through LML, estimation of market power of individual banks becomes feasible, while a number of strong theoretical and empirical assumptions are relaxed. The empirical analysis is carried out on the basis of EMU and US bank data and the results suggest small differences in the market power and efficiency levels of banks between the two samples. Market power estimates indicate fairly competitive conduct in general; however heterogeneity of market power estimates is substantial across banks within each sample. The latter result suggests that while the banking industries examined are fairly competitive in general, the practice of some banks deviates from the average behavior, and this finding has important policy implications. Finally, efficiency and market power present a negative relationship, which is in line by the so-called "quiet life hypothesis".

JEL classification: L11; C14; G21
Keywords: Efficiency, market power, local maximum likelihood

1. Introduction

The empirical modeling of bank efficiency and market power dates back at least to the 1980s, yet it remains an attractive research area from both a micro and a macroeconomic standpoint. Several studies have estimated bank efficiency using production, cost or profit frontiers. Their analysis is based on the appealing concept that operating efficiency may be estimated as an additive component of the stochastic error term.[1] Many other studies used the implications of the new empirical industrial organization (NEIO) literature (see Bresnahan, 1989) to assess the

[1] For an introduction to stochastic frontiers and a review of the relevant literature, see Kumbhakar and Lovell (2000).

competitive conditions prevailing at the banking-industry level. The focal point of the NEIO literature has been the simultaneous estimation of a supply relation and a demand function so as to identify the so called "conjectural variation elasticity" or "conduct parameter", which serves as a measure of market power. Both these branches of empirical modeling experienced a lively development, yet this did not prevent them from remaining fairly separate.[2] At first sight this seems odd as it is now generally acknowledged that market power studies that ignore inefficiency obtain indicators that are potentially severely biased (see e.g. Berg and Kim, 1998). However, besides the implied misspecification, there has also been no particular effort to correlate bank-level measures of market power with efficiency estimates, probably owing to the systematic difficulty in measuring market power exercised by individual banks.

The novel feature of this paper is that it provides a framework for the joint estimation of efficiency and market power at the individual bank-level. Obtaining bank-level estimates of operating efficiency using stochastic or linear-programming frontiers is a relatively easy task. Similarly, using the implications of the NEIO literature, the competitive conditions of banking markets can be estimated at the industry level on the basis of supply and demand equations. By combining these two strands of literature, bank-level estimates of operating efficiency and industry-level estimates of competitive conduct can be obtained simultaneously, even though to our knowledge this has not been implemented to date.[3] Phrased differently, one may estimate a system comprising of a cost function (that is needed to obtain estimates of the marginal cost) and

[2] For reviews of studies of bank efficiency and competition, see Hughes and Mester (2008) and Northcott (2004), respectively.

[3] A number of studies have tested the relationship between efficiency proxies (such as accounting ratios) and price-cost margins (e.g. Demsetz, 1973; Martin 1988) or between frontier efficiency and structural measures of competition (e.g. Berger and Hannan, 1998). However, both accounting ratios and concentration have been shown to be limited measures of efficiency and competition, respectively (see Berger and Humphrey, 1997; Angelini and Cetorelli, 2003).

the usual supply relation and demand function of the NEIO literature, and obtain an estimate for the conduct parameter (at the industry level) and firm-level estimates of efficiency.

Difficulty arises, however, in the estimation of bank-level conduct parameters (firm-specific indicators of market power) and, to this purpose, existing literature proposes estimation of Lerner indices or calculation of the Tobin's q. Yet, use of the former measure encompasses the rather restrictive assumption of a constant marginal cost for the industry or for classes of banks within the industry, which is then used to calculate bank-specific price-cost margins. In turn, estimation of the marginal cost requires further assumptions regarding the functional form of the underlying production relationship. Furthermore, it has been shown recently that parametric stochastic frontier efficiency estimates may be problematic if the specified functional form is not a good reflection of the data (Kumbhakar et al., 2007). This result naturally extends to estimates of the Lerner index, as their derivation requires assumptions related to the shape of the production relationship, and thus similar shortcomings apply.[4] Tobin's q in turn, even though quite useful as a proxy for market power, requires information on the market value of assets that may not be generally available (especially for non-listed companies), while it does not originate from standard industrial organization theory.

In an effort to make progress on the estimation of bank-level market power, using widely available sources of bank data, this paper proposes estimation of the cost-supply-demand system using the principle of local maximum likelihood (LML). LML, introduced by Tibshirani and Hastie (1987), has been recently employed to estimate stochastic frontiers by Kumbhakar et al. (2007) and Kumbhakar and Tsionas (2007). Since LML allows for observation-specific coefficients through localization, the conduct parameter is also made firm-specific and serves as

[4] This holds regardless of the Lerner index being calculated at the bank level or not, or whether efficiency is accounter for in the estimation procedure.

an index of market power possessed by individual banks. In addition, use of the LML principle presents at least two other advantages. First, the restrictive assumption of a global parametric functional form (such as the Cobb-Douglas, translog or Fourier) that is needed to estimate marginal cost is avoided and, hence, the model is robust to such potential misspecification. Second, since the parameters are localized at each observation, flexibility is not an issue and the use of a general linear form for both the supply relation and the demand function gives a clear economic meaning to each and every coefficient that is made firm-specific through localization. Naturally, the above generalizations ease concerns raised in the industrial organization literature by Corts (1999) and Genesove and Mullin (1998) as regards the interpretation of the conduct parameter and, therefore, they may be quite important in drawing robust conclusions about the efficiency and market power levels or their potential relationship.

The empirical framework is constructed in terms of an existing simple theoretical model of the banking industry[5] and is applied to two panels, corresponding to EMU and US banks. The main reasons behind this choice is that (i) there exists a sizeable and comprehensive literature on the measurement of efficiency and market power of banks in these regions, (ii) we have good priors regarding the structure of the specific banking systems and (iii) sufficient data is generally available. The findings indicate that the empirical framework provides quite reasonable estimates for both efficiency and market power. Both banking systems are characterized by moderately competitive practices; however, what could not be uncovered in previous studies is that the distribution of market power of banks within each banking system has a substantial variance (i.e. significant differences in market power are observed between banks). Finally, the bank-level estimates of market power are adversely related with the efficiency scores, a finding that

[5] However, with minor transformations the model applies to any other industry.

conforms to the important implications of the "quite life hypothesis" as formed by Hicks (1935) and tested by Berger and Hannan (1998) on the banking industry.[6]

Besides providing consistent estimates of efficiency and market power, we view the proposed technique as a valuable tool in exploring theoretical relationships in banking that require data on the market power of individual institutions. For example, studies exploring the relationship between market power and (i) privatizations (e.g. Konings et al., 2005), (ii) union bargaining power (e.g. Dobbelaere, 2004), (iii) financial liberalization (e.g. Cetorelli and Strahan, 2006), (iv) efficiency effects of mergers (Gugler and Siebert, 2007) and (v) regulatory restructuring and efficiency (e.g. Fabrizio et al., 2007) may benefit from the suggested approach. As discussed above, this is mainly because the number of observations will be considerably increased since market power estimates are made bank-specific through localization.

The rest of this paper is structured along the following lines. Section 2 provides an overview of the theoretical background and presents the empirical model. Section 3 carries out the empirical analysis in terms of the EMU and US banking sectors and discusses the results. Finally, Section 4 summarizes the main conclusions.

2. Theoretical background and econometric model

2.1. Theory and identification

In this section we provide a method for the joint estimation of market power in outputs and operating efficiency, both at the firm-level. We model the representative bank, but a similar analysis may be carried out for any other industry. Several studies have separately assessed the efficiency and competitive conditions of the banking industry, and this experience provides

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[6] This hypothesis posits that the reduction in competitive pressure in concentrated markets may result in lessened effort by managers to maximize operating efficiency. In addition to this effect, Berger and Hannan (1998) describe other related mechanisms through which market power may result in reduced operating efficiency and higher costs.

useful feedback for the present analysis. However, the present study deviates from previous literature in two ways. First, we opt for the simultaneous estimation of market power and efficiency and second the market power estimates are made firm-specific. We base our approach on the Cournot-type theoretical framework of Uchida and Tsutsui (2005), which has also been employed by Brissimis et al. (2008).[7] In particular, consider a set of i banks, facing at time t industry demand for loans L_t, and seek to maximize the following profit function:

$$\Pi_{it} = r_t^l l_{it} + r_{it}^b b_{it} - r_{it}^d d_{it} - C_{it}(l_{it}, d_{it}) \quad \text{`} \tag{1}$$

where Π are the profits of bank i at time t, r^l stands for the lending rate, l is the value of loans made by individual banks, r^b is the interest rate on bonds b, r^d is the deposit rate, d is the value of deposits and C is the operating cost function. The representative bank's problem is to $\max_{b,l,d} \Pi_{it}$ s.t. $b_{it} + l_{it} = d_{it}$ and the first order conditions for this problem are

$$r_t^l \left(1 - \frac{1}{\eta_t} \theta_{it} \right) = r_{it}^b + \frac{\partial C_{it}}{\partial l_{it}} \text{ and } r_{it}^b - r_{it}^d - \frac{\partial C_{it}}{\partial d_{it}} = 0 \tag{2}$$

where $\eta_t = (r_t^l / L_t)(\partial L_t / \partial r_t^l)$ is the market demand elasticity for loans and $\theta_{it} = (l_{it} / L_t)(\partial L_t / \partial l_{it})$ represents the well-known conjectural variation elasticity of the new industrial organization (NEIO) literature. In theory, the range of possible values for θ is given by (0,1). In the special case of Cournot behavior, i.e. $\partial L / \partial l = 1$, θ is simply the output share of the ith bank. In the case of perfect competition, θ=0; under pure monopoly, θ=1; and, finally, θ<0 would imply pricing below marginal cost and could result, for example, from a non-optimizing behavior of banks in their lending policy.

The first equation of System (2) may be estimated if one has proper data on the yield of government bonds. However, such data is generally unavailable and, therefore, we omit the bond

[7] This framework is an extension of the models put forth by Bresnahan (1982), Lau (1982) and Appelbaum (1982). The discussion here follows Uchida and Tsutsui (2005).

rate from the estimated equation by combining the two equilibrium conditions of System (2). The resulting equation is:

$$r_t^l\left(1-\frac{1}{\eta_t}\theta_{it}\right)=r_{it}^d+\frac{\partial C_{it}}{\partial l_{it}}+\frac{\partial C_{it}}{\partial d_{it}} \tag{3}$$

Following Uchida and Tsutsui (2005), we further simplify our estimated equation by rearranging Eq. (3) and defining $R_{it}=r_t^l l_{it}$ as the revenue of bank *i* generated by loans. This transformation yields the following expression:

$$R_{it}=\left(\frac{\theta_{it}}{\eta_t}\right)R_{it}+r_{it}^d l_{it}+l_{it}\frac{\partial C_{it}}{\partial l_{it}}+l_{it}\frac{\partial C_{it}}{\partial d_{it}} \tag{4}$$

Note that unlike previous studies, the firm-level nature of the conjectural elasticity parameter θ is reserved, which is in fact closer to the theoretical priors of the NEIO literature (see Bresnahan, 1989).

In most of the empirical applications of this type the marginal cost is not available, but has to be estimated on the basis of a cost function. Estimation of a cost function is usually carried out simultaneously with a supply relation similar to Eq. (4) and an appropriate demand function that helps identifying θ from η. Following this paradigm, we specify a translog cost function of the following form:

$$\begin{aligned}\ln C_{it}=\,&a_0+a_1\overline{\ln l_{it}}+\frac{1}{2}a_2(\overline{\ln l_{it}})^2+a_3\overline{\ln d_{it}}+\frac{1}{2}a_4(\overline{\ln d_{it}})^2+a_5\overline{\ln w_{it}}+\frac{1}{2}a_6(\overline{\ln w_{it}})^2+\\ &\mathrm{a}_7(\overline{\ln l_{it}})(\overline{\ln w_{it}})+a_8(\overline{\ln l_{it}})(\overline{\ln d_{it}})+a_9(\overline{\ln d_{it}})(\overline{\ln w_{it}})+e_{it}^C\end{aligned} \tag{5}$$

where *w* is the price of inputs and bars over the variables represent deviations from their means. Substituting the variables and parameters of Eq. (5) into the respective derivatives of Eq. (4), we obtain the following estimable supply relation:

$$R_{it} = \frac{\theta_{it}}{\eta_t} R_{it} + r_{it}^d l_{it} + C_{it}(a_1 + a_2 \overline{\ln l_{it}} + a_7 \overline{\ln w_{it}} + a_8 \overline{\ln d_{it}}) + \\ C_{it} \frac{l_{it}}{d_{it}} (a_3 + a_4 \overline{\ln d_{it}} + a_8 \overline{\ln l_{it}} + a_9 \overline{\ln w_{it}}) + e_{it}^s \tag{6}$$

Finally, in order to identify θ from η, we specify the following inverse loan demand function:

$$\ln r_{it}^l = g_0 - (1/\eta_t)\ln l_{it} + g_1 \ln gdp_t + g_2 \ln ir_t + g_3 \ln macgdp_t + g_4 \ln ta_{it} + e_{it}^D \tag{7}$$

where, *gdp* is real GDP in constant prices, *macgdp* is the capitalization of the stock market over GDP, *ir* is the one-year bond rate and *ta* is total assets (proxy for bank size). The variables *gdp* and *macgdp* are exogenous variables that affect demand and *ir* is a reasonable proxy for the price of a demand substitute for loans (for a thorough discussion on the variables included in the demand equation, see Shaffer, 1993).

At this point, note that this optimization framework implicitly assumes that each bank is operating on its cost function. Yet, there exists an extensive literature on bank-level efficiency suggesting that institutions operate at inefficient levels, which in many cases are quite significant (for reviews, see Hughes and Mester, 2008; Berger and Humphrey, 1997). However, if inefficiency is not taken into account the optimization model may become irrelevant and the corresponding bias may be quite severe as the level of inefficiency increases. This important issue has been first noted by Berg and Kim (1998) and it has also been acknowledged by Koetter and Poghosyan (2008) and Koetter et al. (2008). Most of the previous literature on competition simply disregards this problem and only few studies resort to the inclusion of only efficient firms into the model of competition (e.g. Berg and Kim, 1998). To this end, we allow for inefficiency in the cost function by decomposing the error term e_{it}^C in Eq. (5) to a component *u* related to bank inefficiency and the remaining disturbance *v*. In other words, Eq. (5) is treated as in the standard stochastic frontier analysis (see Coelli et al., 2005), and therefore by estimating simultaneously Eqs. (5), (6) and (7) one can obtain estimates of both firm-level efficiency and industry-level competition.

2.2. Econometric procedure

What remains as a challenge is the identification of the conjectural variations elasticity θ at the bank-level. This is accomplished by drawing on a non-parametric estimation technique, in particular the local maximum likelihood (LML) technique, to estimate the system specified above. To introduce some notation, consider a system of equations, consisting of a vector of dependent variables *y*, a vector of independent variables *x* and a vector of unknown parameters $\rho \in \mathrm{P}$. In vector notation this system can be written as $y_i = \phi(x_i, \rho) + \upsilon_i$, $i=1,\ldots,n$, ϕ is a vector function and $\upsilon_i \sim N(0, \Omega)$. The usual parametric maximum likelihood (ML) estimator is

$$\hat{\rho}_{ML} = \arg\max_{\rho \in \mathrm{P}} : \sum_{i=1}^{n} \ln f(y_i; x_i, \rho) \tag{8}$$

where $f(y_i; x_i, \rho) = -\frac{m}{2}\ln(2\pi) - \frac{1}{2}\ln|\Omega| - \frac{1}{2}(y_i - \phi(x_i;\rho))'\Omega^{-1}(y_i - \phi(x_i;\rho))$, *n* is the number of observations, *m* is the dimensionality of ρ, Ω denotes the standard normal cumulative distribution function. The ML estimator $\hat{\rho}_{ML}$ of ρ maximizes the concentrated log-likelihood function

$$L^c(\rho) = const - \frac{n}{2}\ln|\hat{\Omega}(\rho)| \tag{9}$$

where $\hat{\Omega}(\rho) = n^{-1}\sum_{i=1}^{n}(y_i - \phi(x_i;\rho))(y_i - \phi(x_i;\rho))'$. Its covariance matrix can be computed as $Cov(\hat{\rho}_{ML}) = \left(\sum_{i=1}^{n}\hat{\Phi}_i\hat{\Omega}^{-1}\hat{\Phi}_i'\right)^{-1}$, where $\hat{\Omega} = \hat{\Omega}(\hat{\rho}_{ML})$ and $\hat{\Phi}_i = \frac{\partial\phi(x_i, \hat{\rho}_{ML})}{\partial\rho}$ is the *k* x *m* gradient of the complete system with respect to the parameters evaluated by the ML estimator.

LML estimation of the corresponding non-parametric model involves a number of steps. First, we specify a kernel function of the form $K_H(z)=(2\pi)^{-d/2}|H|^{-1/2}\exp(-1/2z'H^{-1}z)$, $z\in R^d$, where d is the dimensionality of x_i, $H=h*S$, $h>0$ is the bandwidth and S is the sample covariance matrix of x_i. Then, by choosing a particular point $x\in X$, we may solve the following problem:

$$\max_{\rho_0,\mathrm{P}}:$$

$$L_x(\rho,\Omega)=\sum_{i=1}^{n}\{-(m/2)\ln(2\pi)-1/2\ln|\Omega|-1/2(y_i-\phi(x_i;\rho_i(x)))'\Omega^{-1}(y_i-\phi(x_i;\rho_i(x)))\}K_H(x_i-x)$$

$$=-\frac{nm}{2}\ln(2\pi)-\frac{n}{2}\ln|\Omega|-\sum_{i=1}^{n}W_i(x)(y_i-\phi(x_i;\rho_i(x)))'\Omega^{-1}(y_i-\phi(x_i;\rho_i(x))) \tag{10}$$

where $\rho_i(x)=\rho_0+\mathrm{P}(x_i-x)$, $W_i(x)=K_H(x_i-x)$, adopting the normalization $\sum_{i=1}^{n}W_i(x)=1$. A solution to this problem provides parameter estimates $\hat{\rho}(x),\hat{\Omega}(x)$.[8] Also notice that the weights W do not involve unknown parameters (if h is fixed).

We proceed by concentrating the log-likelihood function above with respect to Ω to obtain the following local estimator

$$\hat{\Omega}(x,\rho)=n^{-1}\sum_{i=1}^{n}W_i(x)(y_i-\phi(x_i,\theta))(y_i-\phi(x_i,\theta))' \tag{11}$$

and substituting Eq. (11) in Eq. (8) we obtain

$$L_x^c(\rho)=const-\frac{n}{2}\ln|\hat{\Omega}(x,\rho)| \tag{12}$$

Eq. (10) can be maximized numerically with respect to ρ to obtain $\hat{\rho}(x)$. Notice that the local estimator $\hat{\Omega}(x,\rho)$ is simply the covariance matrix of weighted residuals $(y_i-\phi(x_i,\rho))(W_i(x))^{1/2}$,

[8] Note that we use local linear estimation for the ρs but local constant estimation for Ω. This is due to computational complexity arising from the fact that Ω must be kept positive definite. The same strategy has been followed by Kumbhakar et al. (2007).

so in fact LML estimation of the type proposed here can be described as an iterated SUR estimator in a properly weighted model (the weights are computed in advance).

It is perhaps important to analyze what the methodology described above achieves. First, as the main contribution of the paper implies, we provide a methodology for the joint estimation of market power and efficiency, both at the individual firm level. Note, that in doing so, we implicitly suggest a new method to obtain an index of market power for the individual firms in the sample. This is accomplished because estimates of market power (and of all coefficients) are made bank-specific through localization. Second, we provide parameter estimates $\hat{\rho}(x)$ that depend on x, and therefore the problem of functional form specification in cost models is solved. Third, the covariance matrix Ω is made function of x, so effectively we allow for heteroskedasticity of unspecified, non-parametric form in all error terms of the system. Fourth, precisely because we are able to make all parameters firm-specific, we effectively remove the assumption of normality from the error terms. Last, but not least, the fact that LML (and in fact any other local method) allows for observation-specific parameter estimates suggests a plausible method to identify parameter heterogeneity, which may be of great importance in indicating individual bank strategies. Given all of the above, we feel that this is an extremely general model that solves many of the problems associated with the estimation of NEIO cost-demand-supply systems. Similar arguments have been made by Kumbhakar et al. (2007) and Kumbhakar and Tsionas (2007) for the non-parametric estimation of stochastic frontier models.

At this stage, however, we also need to make a number of critical remarks concerning the proposed methodology. First, the theoretical framework assumes the existence of market power only in the output side. In other words, the possible presence of monopsony power in bank deposits is not accounted for. Within a very similar theoretical framework, Shaffer (1999) showed that in the presence of monopsony power, the degree of monopoly power would be overstated by the estimates, but the overall existence and magnitude of competitive conditions would be accurately reflected. Therefore, even though our specification has the effect of misattributing market power on the input side to that of the output side, no information of policy significance is lost. Second, statistical tests for monopoly or competitive equilibrium (i.e. tests of θ=1 or θ=0, respectively) are not easy to perform. This is because confidence intervals have to be calculated from scratch, a procedure that may be computationally intensive. However, given the fact that the conduct parameter θ provides a continuous index of competition (with higher values reflecting more market power and vice versa) the empirical researcher may be primarily interested in estimating the level of market power and not so much in testing for equilibrium conditions. Finally, note that as with every non-parametric technique, LML has to be applied to large datasets to avoid the so-called "curse of dimensionality". Luckily, this is not an issue for micro-level studies such as ours, where large datasets are relatively easy to find. In contrast, this may be a real obstacle for empirical economists that face small samples.

3. Empirical application

3.1. Dataset

The present study uses two unbalanced datasets of EMU[9] and US commercial banks spanning the period 2000-2007 (summary statistics of the variables used are presented in Table 1). This period covers the climax of a relatively stable and fully liberalized financial environment in both the EMU and US. The depth of the financial system, as measured by the sum of claims as a ratio to GDP, was very similar in both regions in the beginning of our sample period. However, banks are more important financial intermediaries in the EMU. It is noticeable that with regard to

[9] The sample includes the 11 countries that joined the EMU in January 1999 and Greece that joined in 2001.

the relative size of traditional bank intermediation, as measured by the ratio of holdings of bank-related assets to other intermediated assets, the euro area lies about 1.5 times higher than the US.[10]

Following standard practice in banking industry studies (see e.g. Brissimis et al., 2008), we define the price of inputs (*w*) as the ratio of capital and personnel expenses to total assets and the deposit rate (r^d) as the ratio of interest expenses to total deposits. To be consistent with our theoretical underpinnings (remember that this is a Cournot-type model), we assume that the lending rate (r^l) is equal between banks (see e.g. Shaffer 1993; 1999) and we obtain its value from the International Financial Statistics.[11] Note that for the EMU this figure is different between countries, a fact that may be the source of heterogeneity. To account for this and other potential heterogeneity in the macroeconomic and/or institutional environment of the EMU countries we include country dummy variables in the inefficiency term of the cost function as discussed below. In addition, in one of the robustness checks to be discussed in the empirical results section that follows, we also include capitalization (measured by the ratio of equity to assets) and credit risk (measured by the ratio of non-performing loans to total loans) in the cost equation.

Theoretical priors suggest that coefficients on outputs and inputs in the cost function should bear a positive sign. The same is expected for the coefficient on *gdp* (g_1) in the demand equation. If *ir* is interpreted as the price of a substitute for bank loans, then its coefficient should also be positive. Moreover, excess stock market capitalization may decrease loan demand and, therefore, *macgdp* is expected to bear a negative sign. Finally, larger banks are more easily accessible and better recognized by customers, implying that the relationship between the logarithm of *ta* (proxy

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[10] For overviews of the EMU and US banking sectors, see ECB (2007) and Jones and Critcfield (2005) or Bassett and King (2008), respectively.
[11] As a robustness check we also use a bank-level lending rate in the empirical analysis below.

for bank size) and the lending rate should be – in general – positive.[12] All bank-level data were obtained from BankScope. The macroeconomic data were obtained from the World Bank's World Development Indicators and data for *macgdp* from the Beck et al. (2000) database, as updated in 2007. After applying some selection criteria to the original dataset,[13] we end up with two panels of 560 EMU and 528 US commercial banks, corresponding to 2023 and 2112 observations, respectively. For a formal definition of the variables and some descriptive statistics, see Table 1.

3.2. Empirical results

As discussed above, Eqs. (5), (6) and (7) are simultaneously estimated by LML to produce estimates for both efficiency and competition on an observation-specific basis. Implementation of the LML method, as described above, entails an appropriate choice about the bandwidth parameter h.[14] We choose h using the method of cross-validation. Specifically, we solve the LML problem for all data points but for observation j, and define for some $\bar{x} \in X$,

$$\hat{\rho}^j(x,h) = \arg\max_{\rho_0,\mathrm{P}} : \sum_{i \neq j} \ln f(y_i; x_i, \rho_0 + \mathrm{P}(x - x_i))W_i(x) \tag{13}$$

for all j=1,2,…,n. The point $\bar{x}$ is chosen to be the median of the dataset. Then, we pick the h that minimizes $\sum_{j=1}^{n}(y_j - \hat{y}_j(h))^2$, where $\hat{y}_j(h)$ denotes the fitted value of y_j based on h. Cross

[12] These expectations follow from previous literature (e.g. Uchida and Tsutsui, 2005; Shaffer, 1993; 1999), however for various reasons expectations are not always met. For a thorough discussion of these issues, see Shaffer (1999).

[13] In particular, we drop all banks that have missing observations for any of the core variables of the analysis. Furthermore, we disregard the banks with unreasonable high or low price of labor by trimming 3 per cent of the distribution of the respective variable.

[14] Here we follow the discussion in Kumbhakar et al. (2007) and Kumbhakar and Tsionas (2007).

validation can be implemented based on estimation of the full system by e.g. SUR. In doing this, we end up with a bandwidth parameter equal to 0.707.[15]

Another practical issue in the estimation procedure concerns the potential heterogeneity in the environmental conditions faced by European banks, which may directly influence the error component u associated with cost efficiency in Eq. (5).[16] A popular method used to account for this criticism is that of Battese and Coelli (1995), who assume that a number of exogenous variables may directly influence firm efficiency. Under this approach, the inefficiency term u of the error component in Eq. (5) is made a function of exogenous country-specific determinants of inefficiency. In the context of the present analysis, we use a time trend (T) to account for possible trends in efficiency, real GDP per capita (*gdpcap*) to account for inter-country differences in income, the annual inflation rate (*inf*) as a proxy for price stability and an index that accounts for inter-country differences in capital requirements (*caprq*).[17] Note that for the US sample we only use the time trend. Sources and descriptive statistics for these variables are given in Table 1.

Estimation for the two panels is carried out separately and results are reported in Table 2 and in Figures 1 and 2. In Particular, the first column of Table 2 (baseline specification) reports average values of the estimated coefficients, the findings being very close to expectations regarding the sign and magnitude. For example, both inputs and outputs have a positive impact on costs, while the effect of all of the variables in the demand locus meets the expectations

[15] As the method of cross-validation has been criticized by a number of forerunners (e.g. Ruppert et al., 1995), we also experimented with smaller values for h in order to recover the local properties of the true, non-parametric function. Specifically we used h=0.6 and h=0.5, however, the results remained qualitatively similar and, therefore, we report only those obtained when using h=0.707.

[16] For example, Dietsch and Lozano-Vivas (2000) showed that incorporating regulatory and economic variables into the bank efficiency analysis significantly alters the estimated efficiency scores.

[17] We experimented with many other potential exogenous determinants of efficiency, such as the ones proposed by the recent study of Lensink et al. (2008), but it seems that efficiency scores and the rest of the parameters are not sensitive to the inclusion of these variables.

specified in the previous section. In addition, the level of these coefficients is very close to that identified in previous studies of bank efficiency that employ either parametric (see e.g. Lensink et al., 2008) or non-parametric (Kumbhakar et al., 2007) frontiers. Even though we cannot make any comments regarding the significance of the determinants of efficiency if we do not construct confidence intervals, we note that *gdpcap* is negatively related with inefficiency (which is intuitive since in more prosperous countries banks have better access to new technologies), *inf* is positively related (also intuitive as increased costs associated with higher inflation naturally create operative inefficiencies) and *caprq* has a negative but very small coefficient. All in all, the above results enhance our belief about the validity and robustness of the approach followed.

Table 2 also reports average values for market power (θ) and efficiency (*eff*) estimates. Average market power in the EMU stands at 0.297, denoting fairly competitive practice in general but not perfectly competitive (since the value is relatively low but not close to zero). In the US banking sector the average value is 0.157, reflecting an even more competitive environment. These results clearly suggest that differences between the EMU and US are not substantial on this front, although the fact that the importance of banks relative to other financial intermediaries is higher in the EMU (see ECB, 2007) may explain the somewhat higher average θ found for EMU banks. More specifically, whereas the share of holdings of financial assets in financial intermediaries accounted for 65% of total intermediated financial assets in the euro area as of 2004, it accounted for only 48% in the US. This figure probably indicates that financial liberalization eroded market power of US banks to a greater extend than market power in some EMU banks, particularly those with relatively fragmented banking systems (e.g. banking systems of some Mediterranean countries). Overall, these findings reflect similar results with previous literature (see e.g. Bikker and Haaf, 2002; Claessens and Laeven, 2004).[18] Moreover, average efficiency levels are surprisingly close between the two samples (about 0.88 for the EMU and 0.84 for the US), even though these values are not directly comparable since they represent scores relative to the best practice of each sample (see Coelli et al., 2005). Average efficiency increased in both the EMU and the US over the 2000-2007 period, reaching a high in 2006 in both samples (0.92 in the US and 0.94 in the EMU). It is interesting that there is a fall in 2007 especially in the US, which may reflect the beginning of the financial crisis.

We inquire into the robustness of these baseline results in a number of additional ways.[19] First, we experimented with a bank-level lending rate (proxied by the ratio of interest income to total loans) as in Uchida and Tsutsui (2005). The average estimation results (average coefficients) presented in the second column of Table 2 remained practically unchanged; however there exist some outliers, yielding a relatively large variance for the estimated coefficients and the error terms. Therefore, and combined with the flawed theoretical interpretation of our model when we include a bank-level rate, we conclude that precision of the estimates in this case is inferior. Second, instead of using a translog specification for the cost equation, we employ a simple Cobb-Douglas cost function and we manipulate the revenue equation accordingly. Given the fact that LML should not be sensitive to the specified functional form, we do not expect significant changes in the results, which is indeed the case (see third column in Table 2). Another essential concern might be that these results are somehow an artifact of how the frontier models were implemented in terms of the variables used to shape the frontier. To address this issue we re-estimated the model by accounting for capitalization (measured by the ratio of equity capital to total assets) and for credit risk (measured by the ratio

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[18] Note, however, that these analyses were carried out for an earlier period.

[19] As mentioned above, we carried out the analysis using slightly different bandwidths and other exogenous determinants of inefficiency.

of non-performing loans to total loans). Specifically, we used these variables (i) as bank inputs in the cost function, (ii) as determinants of inefficiency and (iii) both as inputs and as determinants of inefficiency. Even though changes of efficiency and market power estimates were not above the 5% threshold, we feel that equity and risk-taking are better viewed as elements of bank decision-making and therefore are more appropriately considered as inputs. The results obtained from this specification are reported in the fourth column of Table 2 and show no significant change in the average coefficients. Efficiency levels are a little bit lower on average, which could be attributed to the increase in the number of inputs. As a final exercise, we consider a model of market power that does not include an inefficiency term in the cost function. The results are reported in the last column of Table 2 and, in line with expectations, report a significant downward bias for θ, since placing all banks on the efficient frontier lowers the level of market power artificially. Hence, we may have to be skeptical regarding industry-specific estimates of market power obtained from empirical studies that do not include an inefficiency term. Given the above, we use the baseline results in the rest of our discussion.

A clearer picture regarding the level and extend of heterogeneity of the bank-specific coefficients is obtained by the diagrammatic representation of the bank-level estimates (the estimates of the baseline equation are used). Figure 1 presents distributions of the estimated coefficients for the main variables of our analysis (we do not report the coefficients on the multiplicative and the error terms in Eqs. 5 and 6 but these are available upon request) that correspond to the EMU sample and Figure 2 the equivalent for the US sample.[20] Interestingly, the distributions of the coefficients of some parameters are quite wide, which implies that there are important differences in bank behavior. The coefficients on loans, deposits and the price of

[20] Another factor that backs up our estimation procedure is that two of the three parameters associated with the distributions of the noise components show large variation among banks, which suggests that estimating a single set of parameters for all banks is problematic (see also Kumbhakar et al., 2007; Kumbhakar and Tsionas, 2007).

inputs are higher amongst the US banks, reflecting a higher response of costs to a change in these variables in the US case. This is probably indicative of the important rigidities present in some of the EMU banking systems, especially compared to the US banking sector that is representative of Anglo-Saxon type. Similarly, the EMU banks reflect a wider dispersion of coefficients pinpointing to the still existent wide differences between the 12 EMU banking systems examined. We expect these differences to diminish only if European (or global) financial integration further develops, however the recent financial turmoil may alter in many respects the national banking conduct.

Similar conclusions are drawn by looking at the distribution of efficiency estimates, as most banks are between 0.6 and 0.95 per cent efficient. The variance of the distribution is a bit higher in the EMU case but differences are negligible, a result reflecting that parameter heterogeneity is considerable but equally important between the two samples. As regards θ, again differences in the variance of the estimates are not large between the two samples. Indeed, most EMU banks have θs between 0 and 0.6, while most US banks have θs between -0.3 and 0.8. This implies that market discipline is higher in the EMU on average, whereas some US banks operate under competitive conditions and a small number of US banks have significant market power. The findings may suggest that the accelerating opening of interstate branches in the US,[21] which resulted in increased consolidation, outperforms the respective of the EMU (following the adoption of the single currency) and that this consolidation led to increased market power for certain banks. It is noteworthy that a small number of US banks is identified with negative coefficients on the market power parameter, a result that shows non-optimizing behavior. A close look in the data reveals that around 80% of these observations correspond to banks

[21] This is the result of the passage in 1994 of the Riegle-Neal Interstate Banking and Branching Efficiency Act, which allowed bank-holding companies to acquire banks in any state and, since 1997, to open interstate branches.

operating in small localized markets. All in all, the considerable variance of the coefficients indicates substantial heterogeneity in the market power of banks and uncovering this type of parameter heterogeneity is one of the attractive features of LML.

Naturally an interesting question that follows the analysis above is what the relationship between efficiency and market power estimates looks like. Figure 3 illustrates this relationship again using the efficiency and market power estimates obtained from the baseline equation. In both the EMU and the US cases the relationship is clearly negative with slopes equal to -0.19 and -0.12, respectively (both correlation coefficients are significant at the 1 per cent level). Therefore, we find significant evidence for the so called "quiet life hypothesis", a finding very similar to that of Berger and Hannan (1998). More specifically, Berger and Hannan provide at least four interrelated reasons about why market power (in terms of industry concentration in their study) and operating efficiency are negatively correlated, while they suggest that associated welfare losses are considerably higher than the losses arising from traditional industrial organization theory on monopoly power. Yet, in spite of the negative relationship between operating efficiency and market power for the average bank, Figure 1 shows that the most efficient banks of the sample possess relatively high market power. This is especially true for American banks, as some obtain values for θ very close to 1. This is probably a noteworthy remark, which may suggest some degree of reverse causality in the relationship between market power and efficiency. Phrased differently, banks with more efficient management or production technologies have lower costs and therefore higher profits, which allows them to gain large markets shares and market power. Notably, this mechanism lies at the heart of the "efficient-structure hypothesis" (see Demsetz, 1973; Peltzman, 1977; Berger, 1995) and may be present additional explanatory endeavor for the high θ observed for the most efficient US banks.

4. Concluding remarks

This study provided an empirical framework for the joint estimation of efficiency and market power of individual banks. The model is applied to the EMU and US banking industries and the findings suggest that most banks are characterized by moderately competitive behavior. In addition, a clear negative relationship is identified between the level of market power and efficiency of individual banks, a result in line with the theory underlying the quite life hypothesis of Hicks (1935). It is worth noting, however, that the most efficient banks possess market power higher than average, a finding consistent with the efficient structure hypothesis. Finally, an interesting result from a policy perspective is that large intra-industry differences are observed in the market power possessed by banks. This certainly calls for different stance of regulatory policies towards banks with different level of market power.

The numerical illustrations suggest that the methodology provides clear economic implications that are in line with theoretical and empirical priors and useful in at east two directions. First, the level of market power of individual firms is quantified and second bank-level evidence is presented for widely debated issues of banking theory. Admittedly, it is quite unclear whether one can draw general implications on the efficiency-competition nexus from the findings on developed banking systems. Naturally, more research is needed that will incorporate the experience in emerging or transition economies. Furthermore, we feel that other policy-related questions on the relationship between bank-level efficiency or – more importantly – market power and a number of economic- or policy-oriented constituents like regulation and risk-taking may be addressed on the basis of the proposed methodology. Since we hope that this study provides a useful tool, this is a desideratum for future research.

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Table 1
Definition and descriptive statistics of the variables

Variable	Definition	Mean		Std Dev	
		EU	US	EU	US
C	Total operating and financial cost	690717	500768	3937154	2673282
l	The value of total loans	9160421	1.23e+07	2.41e+07	4.60e+07
d	The value of deposits and short term funding	1.41e+07	1.66e+07	4.35e+07	5.41e+07
r^l	Lending rate (in percentage)	7.321	6.429	2.269	1.793
br^l	Bank-level lending rate (interest income/total loans)	0.069	0.063	0.371	0.344
r^d	Price of funds (interest expenses/total deposits and short term funding)	0.065	0.053	0.041	0.036
w	Price of inputs (capital and personnel expenses/total assets)	0.039	0.033	0.024	0.019
R	Total operating income	755447	1588389	4154537	6292210
ta	Total assets	2.11e+07	2.14e+07	1.16e+08	9.03e+07
ea	Capitalization (equity/total assets)	0.090	0.084	0.102	0.072
npl	Credit risk (non-performing loans/total loans)	0.023	0.018	0.175	0.149
gdp	Gross domestic product (GDP)	6.46e+09	1.03e+10	2.72e+08	6.55e+08
ir	Government bond yield	4.578	4.838	0.788	0.723
macgdp	Stock market capitalization/GDP	0.827	1.394	0.381	0.190
gdpcap	GDP per capita	24173.5	-	6739.3	-
inf	Inflation, consumer prices (annual %)	2.484	-	0.979	-
caprq	Index of country-specific capital requirements	5.438	-	1.720	-

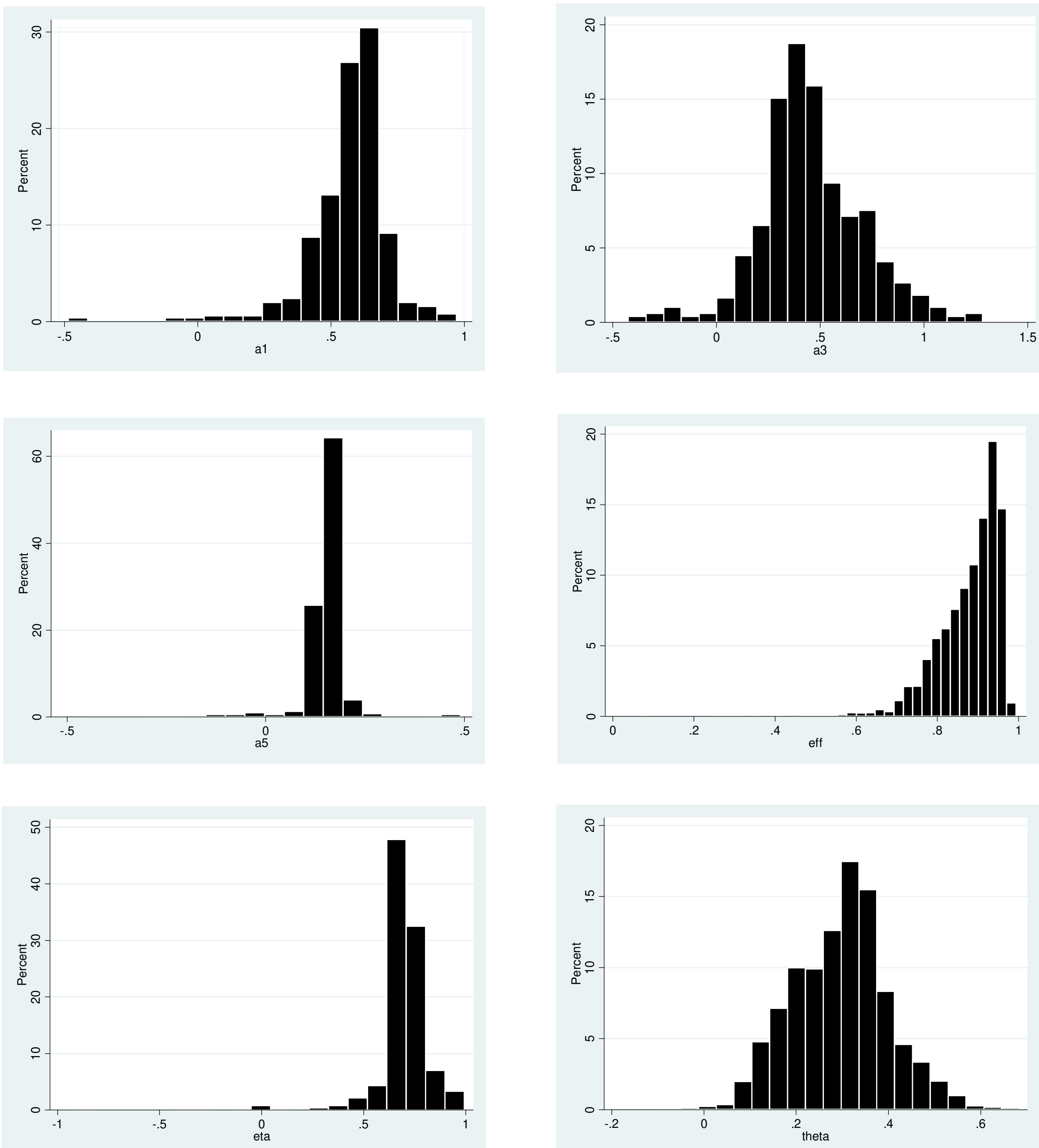
Note: The EMU sample consists of 2023 observations and the US sample of 2112 observations. All figures are expressed in thousand dollars and, were appropriate, the variables have been deflated using GDP deflators. All bank-level variables have been obtained from BankScope. Sources for the rest of the variables are as follows. r^l , *gdp*, *gdpcap*, *inf*: World Development Indicators (WDI); *ir*: International Financial Statistics (IFS), *macgdp*: Beck et al. (2000) database, as updated in 2007; *caprq*: constructed on the basis of the Barth et al. (2001) database, as updated in 2007. The methodology for constructing *caprq* is extensively analyzed in Barth et al. (2001).

Table2
Average coefficients of LML estimation

Variables	EMU	US	EMU	US	EMU	US	EMU	US	EMU	US
	I		II		III		IV		V	
a0	3.042	2.755	3.540	2.873	3.112	2.919	2.814	2.905	2.988	2.645
a1	0.592	0.733	0.550	0.701	0.575	0.731	0.607	0.718	0.681	0.797
a2	0.121	0.203	0.137	0.205			0.130	0.210	0.127	0.222
a3	0.417	0.818	0.397	0.801	0.433	0.805	0.433	0.807	0.384	0.701
a4	0.224	0.186	0.272	0.201			0.242	0.197	0.240	0.103
a5	0.258	0.387	0.266	0.380	0.274	0.370	0.245	0.377	0.115	0.319
a6	0.159	0.234	0.160	0.235			0.146	0.230	0.117	0.210
a7	-0.035	-0.056	-0.042	-0.050			-0.030	-0.041	-0.022	-0.038
a8	0.031	0.044	0.044	0.043			0.037	0.040	0.039	0.045
a9	-0.105	-0.113	-0.112	-0.120			-0.096	-0.101	-0.057	-0.090
ea							0.083	0.097		
npl							0.064	0.051		
η	0.751	0.861	0.747	0.867	0.762	0.852	0.807	0.910	0.609	0.718
θ	0.297	0.157	0.282	0.169	0.290	0.165	0.307	0.186	0.205	0.093
g0	2.773	3.181	2.910	3.145	2.774	3.157	2.539	3.100	2.610	3.003
g1	0.902	1.140	1.010	1.150	0.930	1.134	0.857	1.008	0.864	1.008
g2	0.149	0.212	0.149	0.214	0.147	0.225	0.152	0.207	0.152	0.240
g3	-0.091	-0.143	-0.087	-0.153	-0.088	-0.151	-0.081	-0.137	-0.080	-0.127
g4	0.103	0.069	0.107	0.078	0.112	0.070	0.124	0.072	0.110	0.079
T	0.007	0.012	0.008	0.012	0.007	0.011	0.008	0.014	0.011	0.015
gdpcap	-0.010		-0.011		-0.010		-0.009		-0.018	
inf	0.051		0.055		0.050		0.044		0.067	
caprq	-0.003		-0.003		-0.003		-0.006		-0.005	
eff	0.878	0.835	0.864	0.827	0.869	0.840	0.843	0.819		
σ_v	5.147	4.488	6.728	5.852	5.098	4.470	5.386	4.780		
σ_u	4.021	3.189	7.320	7.015	3.983	3.111	4.129	3.510	8.143	7.530

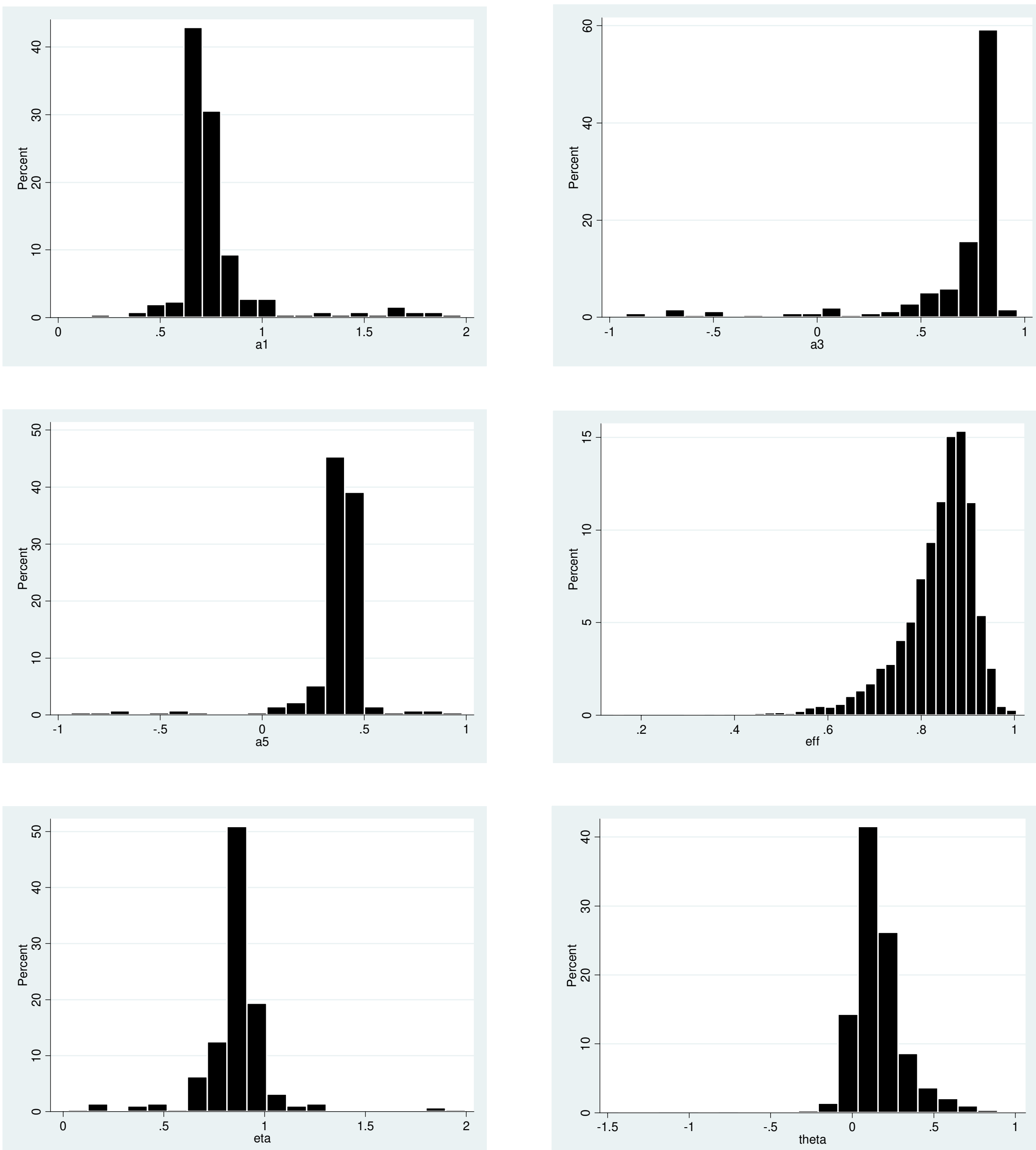
Note: The table presents average coefficients obtained from the estimation of Eqs. (5), (6) and (7). Column I is the baseline equation. In Column II the bank-level lending rate is used instead of the industry-level rate. In Column III the model is specified in terms of the Cobb-Douglas functional form. In Column IV the capitalization (ea) and credit risk (npl) variables are employed as additional inputs of production. In Column V efficiency is not accounted for in Eq. (5) and the model is used to simply estimate market power. The rest of the variables are as follows. T: an annual trend, gdpcap: real GDP per capita, inf: inflation, caprq: index of capital requirements, eff: cost efficiency, σ_u: precision of cost efficiency, σ_v: precision of the remaining disturbance.

Figure 1
Coefficient, market power and efficiency estimates for the EMU panel



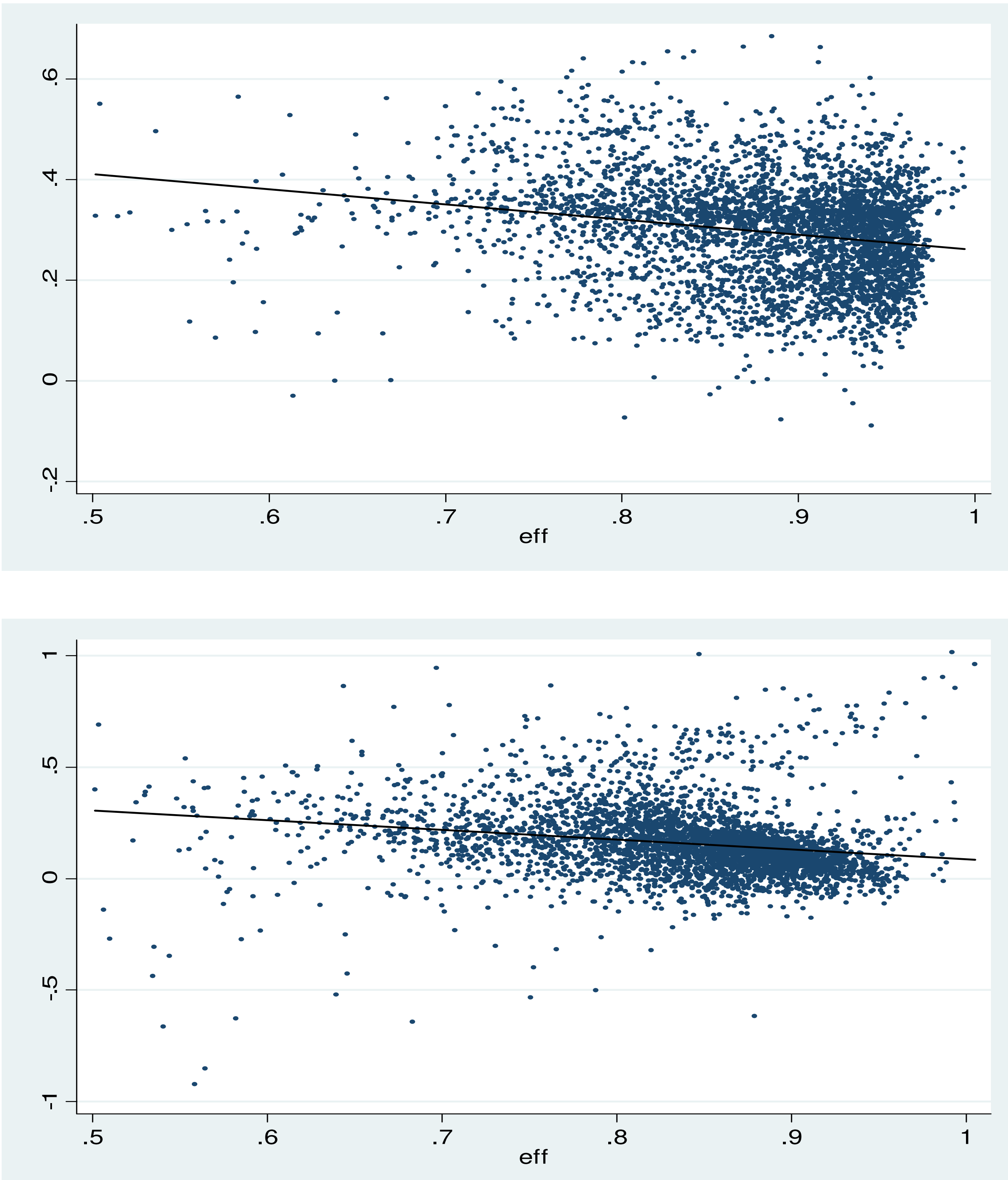
Note: The figures present distributions (in percentage terms) of coefficients obtained from estimating Eqs. (5), (6) and (7) using LML and the EMU panel of banks. a1, a3 and a5 are as in the equations above, *eff* represents the efficiency scores, eta is the market demand elasticity for loans η, and theta represents the conjectural elasticity or market estimates θ.

Figure 2
Coefficient, market power and efficiency estimates for the US panel



Note: The figures present distributions (in percentage terms) of coefficients obtained from estimating Eqs. (5), (6) and (7) using LML and the US panel of banks. a1, a3 and a5 are as in the equations above, *eff* represents the efficiency scores, eta is the market demand elasticity for loans η, and theta represents the conjectural elasticity or market estimates θ.

Figure 3
Relationship between efficiency and market power



Note: The figures plot efficiency estimates (*eff*) against market power estimates (θ), along with the fit of their relationship. The first figure corresponds to the EMU panel and the second to the US panel. The slopes of the fit lines are -0.19 and -0.12, respectively (both significant at the 1 per cent level).