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12

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Please address correspondence to
Banco de Portugal, Financial Stability Department,
Av. Almirante Reis 71, 1150-012 Lisboa, Portugal
T +351 213 130 000 | estabilidade.financeira@bportugal.pt

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Inefficiency Distribution of the European Banking System

João Oliveira
Banco de Portugal
Nova School of Business and
Economics

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Abstract
The inefficiency of the European banking system has been pointed out as a major vulnerability from a financial stability point-of-view. This paper contributes to the assessment of this vulnerability by considering several important features of financial intermediation such as factor prices, economies of scope and scale. We use a stochastic frontier analysis method to characterize the production function of financial intermediation in Europe and quantify inefficiency. We find that: (**i**) in 2013 the median European bank operated with costs 25 to 100% above the efficient level; (**ii**) there is ambiguous evidence on productivity growth, although inefficiency of financial intermediation has been increasing over time, possibly driven by the least efficient banks; (**iii**) increasing returns to scale are limited to smaller banks, although scope savings are found to be robust across all models for the average bank and (**iv**) that there exists a positive association between inefficiency-cost and implicit credit spreads, which are an indicator of credit market restrictions.

JEL: D24, G21, L13

Keywords: Bank efficiency, productivity, frontier analysis.

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E-mail: jholiveira@bportugal.pt

1. Introduction

In the last few years, several institutional reports (e.g. European Central Bank 2016, and European Central Bank 2015) have pointed the European banking system's inefficiency as a major drag on its profitability. Low levels of profit generation capacity among European banks raise concerns as to their ability to withstand major shocks in the future, potentially deteriorating capital ratios and causing a reduction of lending to the economy (see Benes and Kumhof 2015).

Bank inefficiency is also relevant given that it creates a wedge in the the access to credit markets and financial services, which current competition levels are unable to mitigate. In a context where monetary and fiscal policy are constrained in their ability to further stimulate the economy, structural reforms which favour competition or enable lower overheads constitute an alternative for policy-makers seeking to smooth over credit market frictions and reduce counterpart effort levels without a proportional increase in bank risk.

Using a stochastic frontier analysis, as in Boucinha *et al.* (2013), this paper frames the issue of banking system inefficiency for a set of EU Member States by quantifying inefficiency levels, while taking into account several important features of financial intermediation, such as economies of scale and scope, as well as different risk levels across Member-States.

Figures 1 and 2 show the bank-level distribution of cost-to-income and cost-to-assets, respectively, for a sample of European banks in 2013. Compared to the most efficient bank in the sample, European banks operate with 37% and 97% greater costs on average, if measured by cost-to-income or cost-to-assets, respectively. However, this type of analysis does not account for economies of scale or scope, which could explain the large average distance from the most efficient bank as well as the observed dispersion in both distributions. The rate paid on liabilities, which could reflect country-level risk, is also ignored and is likely to be very different across banks in different Member States.

To analyze banks' profit generation capacity, cost-to-income is likely the most relevant measure due to its direct relationship with bank revenues, as opposed to cost-to-assets which is a measure of average costs per unit of output. However, its dependence on the income component is a disadvantage, as it creates a channel through which a bank's risk-taking can distort measurement of efficiency, i.e., a bank that grants loans to a riskier counterpart will demand a higher interest rate than another which is equally efficient but more risk-averse. Although a positive relationship exists between the rate charged on loans and the one paid on interest-bearing liabilities which could offset the effect of higher risk, that relationship is neither one-to-one nor constant through time (Figure 3). This is due to different levels of market power across banks and, more recently, to greater funding of banking groups by central banks at lower than market rates.

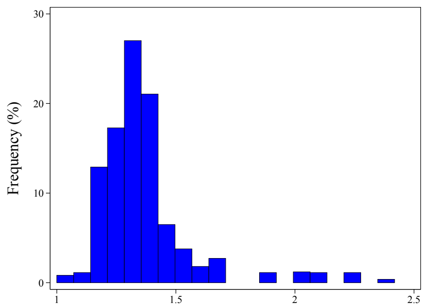


FIGURE 1: Cost-to-income distribution

Notes: Cost-to-income is the ratio between total costs (interest and overheads) and income net of impairments averaged over each bank. The distribution shows cost-to-income as a proportion of the bank which displays the lowest value for that indicator.
Sources: Bankscope.

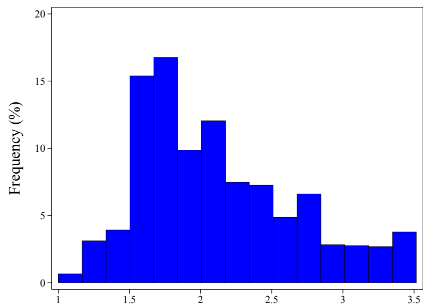
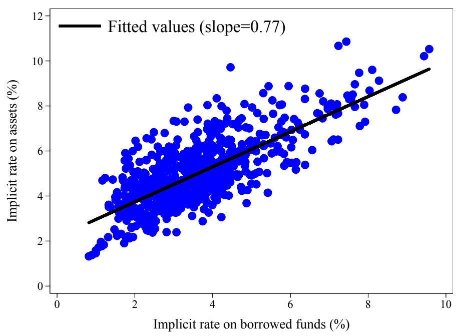
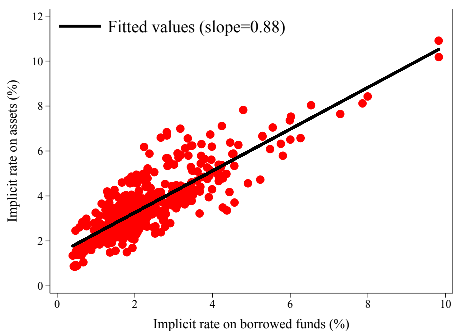


FIGURE 2: Cost-to-assets distribution

Notes: Cost-to-assets is the ratio between total costs (interest and overheads) and income-generating assets averaged over each bank. The distribution shows cost-to-assets as a proportion of the bank which displays the lowest value for that indicator.
Sources: Bankscope.



(A) 2001 – 2008



(B) 2009 – 2013

FIGURE 3: Risk and required return

Notes: implicit rates are measured as the ratio between interest received (paid) and interest-bearing assets (liabilities).

Using a stochastic frontier method, as proposed in Boucinha *et al.* (2013), we are able to take these issues into account and produce bank-level estimates of inefficiency for our definition of financial intermediation, i.e., using funding, labour and physical capital to grant credit to the economy. The outcome variable is, therefore, the quantity of earning assets net of impairments on banks' balance sheets. We argue that this is a more stable outcome variable than the elements of the income account, which are often subject to numerous temporary adjustments and have a high correlation with risk. That being said, there are also significant drawbacks such as different securitization practices across Member States, which affect the level of on-balance sheet credit, as well as the presence of non-performing exposures (NPE). As bank-level data on off-balance sheet commitments and NPEs is not available in our data set, this has the potential to bias inefficiency estimates upward for those banks which engage more in securitization and downwards for institutions which have higher NPEs which have not been registered as impaired. We attempt to deal with these issues by using the framework suggested by Greene (2005) to account for individual-specific effects.

By using our estimates to rank banks we avoid employing income as a measure of outcome and are less liable to mistake risk-taking for higher productivity. This is achieved in two ways: (i) by considering alternative indicators for the cost of funding and (ii) using the fixed and random effects framework proposed by Greene (2005) to account for any time-invariant heterogeneity. One of our main contributions to the literature is to argue that using a bank-specific implicit rate on liabilities as a proxy for the price of funding is not exogenous to a bank's inefficiency level and to propose alternative indicators, such as the median implicit rate on liabilities in a given Member State and the money market rate. We show that these alternative assumptions are non-trivial for the estimation of the inefficiency distribution.

From our baseline model we calculate that European banks in 2013 were operating, on average, with 74% greater costs than the frontier. The comparable figure is 97% in cost-to-assets. Across the estimated models, we find no evidence of economies of scale in banking but we do find some indication of economies of scope. We also find that inefficiency has been on the rise during the $2001-2013$ period, although this is being driven by the most inefficient units in the sample. Findings on the statistical significance of total factor productivity growth are mixed, but costs have been declining systematically, on average.

Finally, inefficiency estimates, which will ultimately be used to sort banks into a ranking and allow us to evaluate them with respect to their peers, are highly correlated with each-other. This indicates that the ranking is robust to alternative assumptions regarding both the price of funding and the way that bank-specific effects are modelled.

The paper is organized as follows: Section 2 presents the theoretical backdrop for the inefficiency model and the estimation method. Section 3 discusses available data and the sample used. Section 4 presents the results and a discussion on the presence of individual effects. Section 5 concludes.

2. Methodology

Following Boucinha *et al.* (2013), we adopt the intermediation approach to bank production (Sealey and Lindley 1977) which considers lending and investment in securities as the main activity of credit institutions. Deposits and other funding are viewed as inputs along with physical capital and labour. This is in contrast to the production approach where banks are regarded as providers of both credit and savings services.[1] As we cannot empirically implement a production or a cost function in which deposits appear simultaneously as inputs and outputs, as pointed out in Hughes *et al.* (2001), these two possibilities must be modelled separately. For brevity, we choose to model only the former.

We diverge from Boucinha *et al.* (2013) in that we do not model a cash-flow cost function, i.e., a cost function conditioned on the level of equity (see Hughes *et al.* 2001 for additional details). The reason is that we do not find evidence in the data that a higher level of equity is associated with lower amount of interest paid when controlling for the price of funding. Therefore, we are implicitly excluding the funding structure from the estimation of the cost function.

In the interest of clarity, we briefly describe the modelling of the production function and its relationship with the cost function. We follow Boucinha *et al.* (2013), which use the model by Battese and Coelli (1992) in their study. In the absence of inefficiency or measurement error, firm i in period t produces:

$$y_{it} = f(x_{it}; \beta)\,, \tag{2.1}$$

where y_{it} is the quantity of output, x_{it} is the input vector, β is the parameter vector and f is the deterministic production function. In practice, however, a firm produces less than the theoretical maximum due to inefficiency (e.g. bad management):

$$y_{it} = f(x_{it}; \beta)\xi_{it} \exp(\nu_{it})\,, \tag{2.2}$$

where $\xi_{it} \in (0, 1]$ captures inefficiency and varies across i and t. Hence if $\xi_{it} < 1$ the firm is producing below its theoretical maximum. ν_{it} is a random error component. [2] To be able to estimate β, we apply the natural log transformation to 2.2, making the expression linear in parameters:

$$\ln y_{it} = \ln\big(f(x_{it}; \beta)\big) + \ln \xi_{it} + \nu_{it}\,. \tag{2.3}$$

1. To motivate their choice, Boucinha *et al.* (2013) carry out an exercise proposed in Hughes and Mester (1993): if the elasticity of other variable costs (remuneration of other borrowed funds, physical capital and labour) to the level of deposits is negative, then deposits should be seen as an input. Boucinha *et al.* (2013) find that this is the case for the Portuguese banking system. Intuitively, increasing the level of an output should also increase the total amount of variable costs if the cost function is continuous. We are unable to replicate this exercise, as data on interest paid on deposits is unavailable.

2. The exponentiation of ν_{it} guarantees that $y_{it} \in \mathbb{R}^{++}$ for any assumed distribution for ν_{it} on $\mathbb{R}$.

Assuming that the production function f is well approximated by a linear function we write:

$$\ln y_{it} = \beta_0 + \sum_{j=1}^{k} \beta_j \ln x_{jit} - u_{it} + \nu_{it}\,, \tag{2.4}$$

where $u_{it} = -\ln(\xi_{it})$. This transformation implies that $u_{it} > 0$, given that $\xi_{it} \in (0,1]$, and it measures the inefficiency of firm i at t: the higher u_{it}, the higher is inefficiency, all else equal.

Because of data limitations on the number of workers and amount of physical capital for each firm, we choose to model the cost rather than the production function of financial intermediation. By the Duality Theorem, we are able to extract the same information from the cost function as we would have from the production function. This is due to the equivalence between profit maximization and cost minimization problems.[3] Starting from the dual of 2.4 and by applying the same transformations, we obtain:

$$\ln C_{it} = \delta_0 + \delta_1 \ln y_{it} + \sum_{j=2}^{k} \delta_j \ln \omega_{jit} + u_{it} + \nu_{it}\,, \tag{2.5}$$

where C_{it} is total cost and ω_{jit} is the price of input j for firm i at t.

This equation is the basic object in this paper, as we are interested in estimating u_{it}. As this quantity is unobservable and indistinguishable from ν_{it}, stochastic frontier analysis relies on distributional assumptions on both elements of $U_{it} = \nu_{it} - su_{it}$ (where s is positive for a production function and negative for a cost function). Battese and Coelli (1992) propose multiple approaches for the estimation of 2.5 using unbalanced panel data. We can assume that inefficiency is time-constant and well approximated by a truncated normal distribution, i.e., $u_{it} = u_i$ and $u_i \sim \mathcal{N}^+(\mu, \sigma_u^2)$, with $\nu_{it} \sim \mathcal{N}(0, \sigma_\nu^2)$, independence between the unobservables and exogeneity of any additional regressors included. Alternatively, we choose to model inefficiency as a time-varying quantity, which changes according to a decay factor:

$$u_{it} = \exp[-\eta(t - T_i)]u_i\,, \tag{2.6}$$

where T_i is the last available period for firm i and η is the decay factor. Thus, inefficiency increases through time if $\eta < 0$, it is time-constant if $\eta = 0$ and decreases if $\eta > 0$. We use the technical inefficiency estimator proposed by Battese and Coelli (1988):

$$CI_{it} = E\Big[\exp(u_{it})|U_{it}\Big]\,, \tag{2.7}$$

3. See Mas-Colell *et al.* (1995) for a proof assuming no inefficiency. Under the possibility of inefficiency, see Kumbhakar and Lovell (2000).

i.e., we obtain an estimate of inefficiency though the distributional assumptions made on u_{it} and ν_{it}, conditional on the observed U_{it}. We can express cost-inefficiency in more intuitive manner (Battese and Coelli 1988):

$$CI_{it} = \frac{E[C|u_{it}, X_{it}]}{E[C|u_{it} = 0, X_{it}]}\,, \tag{2.8}$$

which is the ratio between the cost level with which a firm operates and the minimum cost it would operate with, assuming no inefficiency exists and conditioning on the exogenous regressors X_{it}. Note that $CI_{it} \in [1, +\infty)$, where unity indicates a fully efficient firm. A value of 1.2 indicates that it is operating with costs 20% above the estimated minimum cost frontier. It is this quantity that we aim to estimate in order to evaluate the inefficiency of the European banking system.

To implement this model we require a specification for 2.5. Following Boucinha *et al.* (2013), we assume banks choose variable inputs so as to minimize total costs, subject to the production of a given quantity of loans, other earning assets and exogenous factor prices. The cost function is then the value function of this problem:

$$\begin{aligned}
&C(y_1, y_2, \omega_F, \omega_L, \omega_K) = \min_{F,L,K} (\omega_F F + \omega_L L + \omega_K K)\\
&s.t.\\
&f(x) \geq \bar{y}\\
&\omega_F, \omega_L, \omega_K > 0\,,
\end{aligned} \tag{2.9}$$

where,

$$\begin{aligned}
C &\equiv \sum_{m\in x} \omega_m m; & x &= \{F, K, L\}\\
y_1 &: \text{Net loans;} & y_2 &: \text{Net other earning assets;}\\
\omega_m &: \text{Price of input } m \in x; & F &: \text{Funding;}\\
L &: \text{Labour;} \quad K : \text{Physical capital}\,.
\end{aligned} \tag{2.10}$$

A stochastic version of the value function is given by:

$$\ln C_{it} = \ln\left[C(y_{1it}, y_{2it}, \omega_{Fit}, \omega_{Lit}, \omega_{Kit})\right] + u_{it} + \nu_{it} \tag{2.11}$$

Following Boucinha *et al.* (2013) we assume 2.11 to have a translog functional form, which is a second order local approximation to the solution of

2.9 for the average bank. Rewriting 2.11:

$$
\begin{aligned}
\ln C_{it} = {} & \delta_0 + \gamma_t t + \frac{1}{2}\gamma_{t,t} t + \sum_{j=1}^{2} \delta_{t,j} t \ln y_{jit} + \sum_{m \in x} \delta_{t,m} t \ln \omega_{mit} \\
& + \sum_{j=1}^{2} \delta_j \ln y_{jit} + \sum_{m \in x} \delta_m \ln \omega_{jit} + \frac{1}{2} \sum_{j=1}^{2} \sum_{s=1}^{2} \delta_{j,s} \ln y_{jit} \ln y_{sit} \\
& + \frac{1}{2} \sum_{m \in x} \sum_{l \in x} \delta_{m,l} \ln \omega_{jit} \ln \omega_{sit} + \frac{1}{2} \sum_{j=1}^{2} \sum_{m \in x} \delta_{j,m} \ln y_{jit} \ln \omega_{mit} \\
& + u_{it} + \nu_{it} \,,
\end{aligned} \tag{2.12}
$$

where the interaction term between the two outputs produced, $\ln y_{1it} \ln y_{2it}$, measures economies of scope. Intuitively, banks can dilute the fixed costs of, for example, a credit risk analysis department by granting both loans and buying securities, thereby lowering average costs. We also assume that:

$$
\delta_{j,s} = \delta_{s,j}, \forall j, s; \quad \delta_{m,l} = \delta_{l,m}, \forall l, m \,, \tag{2.13}
$$

which is a symmetry requirement on the coefficients. Unlike Boucinha *et al.* (2013), we do not impose additional restrictions on the relationships between coefficients, which are required in order to have a consistent measurement of marginal costs, for example. This is because we are interested in modelling the cost function only for the evaluation of efficiency and productivity.

We use the maximum likelihood estimator proposed in Battese and Coelli (1992) to estimate different versions of 2.12. As usual, maximum likelihood estimators are consistent only if the imposed distributional assumptions are correct.

3. Data

We use accounting data from Bankscope on the largest banks from a group of 15 EU Member States for the $2000 - 2013$ period.[4] This yields an unbalanced panel with 122 institutions and a median of 14 periods by institution, with a total of $1,505$ observations.

We remove all observations of institutions which are classified as *specialized government lending institutions* by Bankscope, which include, for example, the Irish Bank Resolution Corporation. Observations for institutions where the ratio of loans to assets is lower than 10%, on average, are dropped as well.[5] To

4. Member States are Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden and the United Kingdom.

5. This includes a number of banks which mainly engage in wealth management. We also remove a local subsidiary of a banking group whose main function is to hold the derivatives of the whole group.

ensure consistency between models, we drop observations for which information on costs, output and input prices are not simultaneously available.[6] This yields a sample of 110 institutions and a median of 13 periods, with a total of $1,243$ observations.

Construction of variables used to estimate 2.12 is as follows:

- $\mathbf{y_1}$: loans net of impairments, excluding interbank loans. In contrast to Boucinha *et al.* (2013) no correction for loan securitization is made, as that information is unavailable;
- $\mathbf{y_2}$: other earning assets net of impairments, which include interbank loans, derivatives and other financial assets generating interest or dividends;
- $\boldsymbol{\omega_F}$: Boucinha *et al.* (2013) use the ratio between total interest paid and the value of liabilities as a proxy for the price of funding, denoted by ω_{F1}. We argue that this indicator may not be exogenous given that bank credit ratings, which influence funding prices, are partly determined by the certainty of future cash-flows, which is affected by a bank's efficiency. This implies that ω_{F1it} and u_{it} in 2.12 are correlated. Inefficiency may thus be underestimated for banks which incur higher funding costs. Alternatively, we use the median implicit interest rate on liabilities by Member State in each year (ω_{F2}, reflecting overall risk in a bank's home market) or the local money market rate (ω_{F3}), which are more likely to be exogenous to an individual bank's inefficiency;
- $\boldsymbol{\omega_L}$ and $\boldsymbol{\omega_K}$: no information is available for the number of workers or the amount of physical capital. Thus, we assume that whatever price differences exist are reflected in the value of y_1 and y_2 (,e.g., if the price level of labour or capital is higher in a Member State then, all else equal, the value of loans granted will also be higher). This implies that these factor prices will not be included in estimation;
- **C**: sum of interest paid and overheads.

Table 1 shows summary statistics for the main variables to be used in estimation of the stochastic frontier. The data are then expressed as log-deviations from the mean so that it fits 2.12 and coefficients can be interpreted as partial effects at the mean. Table 2 contains measures of the weight of sample banks relative to total banking system assets in each member state. The representativeness of our sample to total banking system assets ranges from 45% in the UK to 100% in Greece, yet for most member-states it is above the 75% threshold. This indicates that sampled banks represent a very relevant fraction of total lending in the $\mathrm{EU}-15$.

6. We also use two year moving averages for bank output, which implies that one year is lost from the sample.

	Obs.	Mean	Std.dev.	Min.	Max.
y_1	1,243	115,553	128,987	1,269	724,022
y_2	1,243	125,487	223,573	154	1,630,582
w_{F1}	1,243	3.07	1.77	0.41	19.51
w_{F2}	1,243	2.89	1.10	0.86	7.35
w_{F3}	1,243	2.47	1.52	0.22	5.96
C	1,243	9,443	12,447	125	105,699

TABLE 1. Summary statistics

Notes: all variables are in millions of euro, with the exception of the price of funding proxies which are in percentage points.
Source: Bankscope.

Member-state	% total assets	Member-state	% total assets
Germany	51	Netherlands	90
Austria	86	Italy	57
Denmark	83	Ireland	76
Belgium	77	Luxembourg	NA
Spain	78	Portugal	80
Finland	83	United Kingdom	45
France	86	Sweden	80
Greece	100		

TABLE 2. Sample bank assets by Member-state

Notes: total assets are total banking system assets from Moody's banking system reports/outlooks for either 2013 or the last available year.

4. Results

4.1. Model-based approach

To account for risk in the measurement of inefficiency in an explicit and consistent manner, we run different versions of 2.12 with distinct proxies for the price of funding, as mentioned in the previous section. Table 3 shows estimation results, where we omit most of the terms for simplicity.

Models 1 and 2 implicitly assume that all input prices are the same for all banks and do not change through time. In what concerns the price of funding, this is clearly a strong assumption, as banks that choose to operate in riskier segments, and thus have higher funding costs, are not necessarily more inefficient than their counterparts. Ignoring this feature creates a distortion

	(1)	(2)	(3)	(4)	(5)	(6)
t	-0.05***	-0.05***	-0.04***	-0.02	-0.02	-0.07**
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)
$\ln y_1$	0.51***	0.51***	0.58***	0.61***	0.62***	0.47***
	(0.08)	(0.08)	(0.03)	(0.06)	(0.07)	(0.09)
$\ln y_2$	0.47***	0.47***	0.37***	0.35***	0.35***	0.51***
	(0.06)	(0.07)	(0.02)	(0.06)	(0.05)	(0.07)
$\ln y_1 \times \ln y_1$	0.09***	0.09***	0.06***	0.07***	0.07***	0.09***
	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)
$\ln y_1 \times \ln y_2$	-0.15***	-0.15***	-0.09***	-0.11***	-0.10***	-0.15***
	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)
$\ln y_2 \times \ln y_2$	0.06***	0.06***	0.05***	0.05***	0.04***	0.06***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
$\ln \omega_{F1}$			0.64***			
			(0.04)			
$\ln \omega_{F2}$				0.56***	0.56***	
				(0.10)	(0.10)	
$\ln \omega_{F3}$						0.40***
						(0.09)
μ	0.29	0.00	0.71***	0.44	0.00	0.62**
	(0.51)	(0.00)	(0.19)	(0.64)	(0.00)	(0.30)
η	-0.09***	-0.09***	-0.03**	-0.08***	-0.08***	-0.09***
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
Obs.	1,243	1,243	1,243	1,243	1,243	1,243
Log-likelihood	-107.55	-108.02	968.57	126.64	124.20	58.30
γ	0.83	0.88	0.87	0.81	0.90	0.84
σ^2	0.33	0.46	0.07	0.20	0.37	0.25
σ_u	0.52	0.63	0.24	0.40	0.58	0.46
σ_ν	0.24	0.24	0.09	0.19	0.19	0.20
Wald tests						
$\eta = \mu = \gamma = 0$	0.00	0.00	0.00	0.00	0.00	0.00
$\eta = \mu = 0$	0.00	0.00	0.00	0.00	0.00	0.00
$\mu = 0$	0.56	.	0.00	0.49	.	0.04
$\eta = 0$	0.00	0.00	0.01	0.00	0.00	0.00

Bootstrap standard errors in parenthesis
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3. Cost frontier estimates: scale and factor prices

Notes: γ is the fraction of the variance of the dependent variable due to inefficiency. σ^2 is the variance of the dependent variable. Remaining estimates are as per the notation on Section 2. The Wald test section shows tests' p-values.

whereby inefficiency is over-estimated for those banks which are subject to an overall higher level of interest rates on liabilities.[7]

7. This also affects the position of the cost frontier itself.

Model 1 is estimated without restricting u's distributional parameters. We run Wald tests to determine whether the unrestricted model is an accurate description of the data (see the bottom of Table 3). The null hypothesis that inefficiency does not exist ($\eta = \mu = \gamma = 0$) is rejected. In fact, this hypothesis is strongly rejected in every model presented on the table, indicating that existence of inefficiency is robust to the different specifications.

The hypothesis that the mean of the distribution of u is zero is not rejected, prompting us to estimate Model 2, which includes a zero restriction on the mean. In what concerns the time-varying properties of the distribution of u we find that the sample of European banks is becoming more inefficient over the period, as per our estimate of η which is negative and statistically significant. This finding is robust for every specifications of this table.

In what concerns total factor productivity, i.e. contraction of the cost function over time, we find a negative coefficient for the trend term t in every model, although the significance of the estimate cannot be assured for models 4 and 5.

Model 3 includes a control for the implicit rate on liabilities at a bank-level, as in Boucinha *et al.* (2013). If the relationship between total costs and this rate is well-approximated by a second degree polynomial (as we assume), this model reduces the notion of inefficiency to overheads, i.e., so-called operational costs. This is because all changes in funding costs are explained by either changes in output or in price. This addition to the model increases the likelihood of the estimated cost function, which suggests that prices play an important role in the determination of a bank's total costs.[8] In this specification, $\mu = 0$ is rejected, indicating that the overall mass of banks is located away from the minimum cost.

Models 4 through 6 attempt to address the endogeneity concerns raised in the previous section by using the median implicit interest rate levels, ω_{F2}, and the local money market rate, ω_{F3}, as exogenous funding costs. This decreases the likelihood of the models when compared to model 3, given that ω_{F1} is mechanically correlated to the dependent variable. We find that the estimated coefficient for the exogenous funding price is lower for models $4-6$ when compared to model 3 albeit by a small amount. However, using these alternative indicators implies a different shape for distribution of u. This is to be expected, as each indicator affects the estimation of the frontier. By using ω_{F2}, we are penalizing banks which diverge from their market-specific median interest rate on liabilities.

In contrast, the use of ω_{F3} assumes that the financing rate is the same for all banks in a currency area in a given year. Out of the three available indicators, this is the most restrictive as it is not correlated with most bank-level changes in the total amount of interest paid. Thus, it may account for changing costs

8. An unsurprising find, given that the two indicators are correlated by construction.

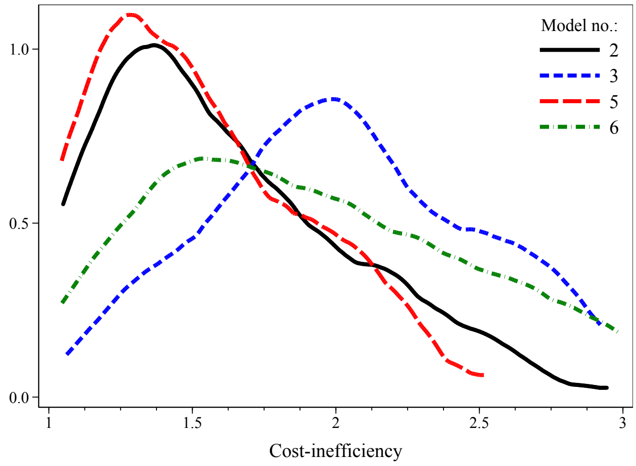


FIGURE 4: Cost-inefficiency distributions

Note: distributions of cost-inefficiency in 2013 estimated through 2.7 based in the models on Table 3.

across time, but hardly for any differences across sample banks. The advantage of ω_{F3} is that its exogeneity with respect to a particular bank's inefficiency is hardly debatable, as reference rates are heavily influenced by monetary policy and are uncorrelated with an individual bank's efficiency.

Thus, we view ω_{F2} as the most appropriate indicator due to both its prospective exogeneity and to the way it penalizes banks' performance. For this reason, we view model 5 as being the closest to the true model and consider it the baseline for the analysis.

Figure 4 plots estimated inefficiency densities in 2013 for a selection of the estimated models. Table 4.1 presents summary statistics for these distributions.

	Obs.	Mean	Std.dev.	$25^{\text{th}*}$	Median	$75^{\text{th}*}$
Model 1	96	1.90	0.80	1.34	1.65	2.38
Model 3	96	2.12	0.54	1.81	2.06	2.40
Model 5	96	1.74	0.69	1.29	1.57	2.08
Model 6	96	2.26	0.98	1.53	2.04	2.82

Note: * percentiles of the inefficiency distribution.

TABLE 4. Inefficiency distribution summary statistics

Resulting densities have significant differences, implying that the use of alternative cost of funding indicators is non-trivial for the distribution of inefficiency. The baseline model (model 5) yields a distribution where half of the mass of banks lies below a 57% inefficiency level. In contrast, half of estimated inefficiencies for models 3 and 6 are below the 100% mark. Although using ω_{F1}

is less restrictive than using the other two indicators in terms of penalizing banks' observed costs it also affects the rendition of the cost frontier and the relative distance between estimated inefficiencies.

In what concerns the features of the cost function, we find that economies of scope exist at the mean and are robust to the different specifications, as can be observed by the negative and statistically significant coefficient on the interaction between output types ($\ln y_1 \times \ln y_2$). Scale economies can be measured by summing up the elements of the gradient of the cost function with respect to output:

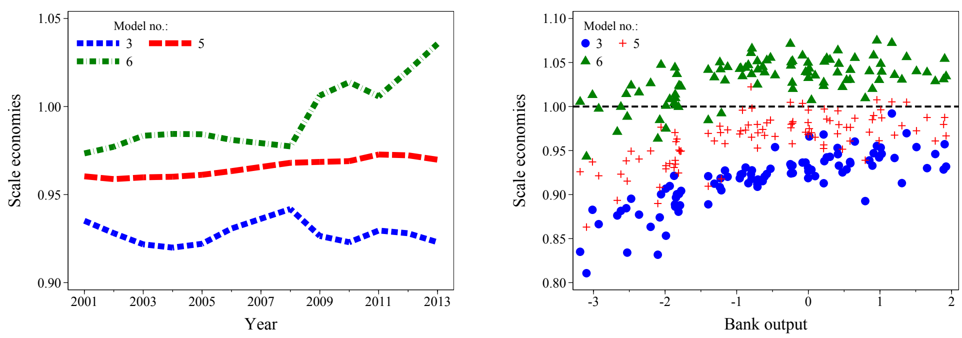
$$SE_{it} = \sum_k \frac{\partial \ln C_{it}}{\partial \ln y_{kit}}, \quad k = 1, 2\,. \tag{4.1}$$

Table 5 displays the estimated economies of scale indicator (4.1) at the mean and the significance of that value for every model on Table 3.

	(1)	(2)	(3)	(4)	(5)	(6)
Wald test	0.96	0.92	0.40	0.78	0.80	0.97
SE (at the mean)	1.00	0.99	0.97	0.98	0.98	1.00

Table 5. Scale economies estimates

Notes: Table presents Wald test p-values and scale economies at the mean of $\ln y_1$ and $\ln y_2$.



(A) Across time

(B) Across banks in 2013

Figure 5: scale economies across dimensions

Notes: Scale economies are measured as the elasticity of costs to total output. The higher the elasticity, the lower the scale economies. (A) shows average scale economies across time. In (B) scale economies are measured for each bank using 4.1. Bank output is the log of total earning assets.

The evidence on Table 3 shows that for none of the estimated models do we find economies of scale, with costs increasing one-for-one with output.

Figure 5 shows the variation of scale economies across dimensions. Across time, model predictions are rather stable, but centered around distinct levels. Calculating elasticities for 2013 alone and observing their behaviour across banks with different outputs, we can see that the estimates of model 3 remain below unity for every single bank in the sample. Estimates from models 5 and 6 display a different behaviour, with a large fraction of banks close to or above the unity line, implying that constant returns to scale in bank intermediation cannot be ruled out. Scale economies appear to be negatively correlated with bank output. This suggests that there might be gains from banking system consolidation among the smaller banks, although this observation is not robust to the different specifications.

One interpretation of these results could be that scale economies are more likely when operational costs are considered in isolation, which is the implicit assumption in model 3. However, if funding and other inputs are substitutes, it could be the case that the savings that the model interprets as economies of scale are in fact a shift to funding in the input combination due to lower prices. Intuitively, some banks will be clustered around a lower overall level of operational costs because they made a decision to shift a significant fraction of their input combination to funding.

In the case of models 5 and 6, because funding prices do not co-move mechanically with funding costs, changes in the latter are absorbed be either the residual or the remaining regressors. In particular, a larger fraction may be explained by changes in output. Estimated coefficients in models 5 and 6 reflect this phenomenon, which can explain why increasing returns to scale are less likely.

4.2. Inefficiency under alternative assumptions

The empirical productivity analysis literature (in particular, Greene 2005) points to an important conceptual pitfall associated with the models estimated in the previous section: The existence of time-invariant unobserved heterogeneity which co-exist with, but are separate from, inefficiency. This may result from different operating settings between production units, such as business models or local regulation and supervisory practices. Although there has arguably been a drive towards regulatory and supervisory harmonization in Europe, culminating in the Single Supervisory Mechanism in 2014, accounting for these differences is desirable as a robustness check.

This type of model miss-specification may result in two practical problems: (i) mistaking legitimate heterogeneity in cost structures with inefficiency if the true model has random effects and (ii) inconsistent parameter estimators if the model is a fixed effects model. (i) is more conceptual in nature, in the sense that there is no test to check whether random effects exist separately from inefficiency or not but rather whether it makes theoretical sense to allow for them. Given the underlying heterogeneity due to business models and local regulations between banks in different Member States, the existence of these effects is certainly a possibility. (ii) is a more technical problem which arises when the individual-specific effects are correlated with regressors.

Following Greene (2005) we can recast 2.5 as a true fixed effects model:[9]

$$\ln C_{it} = \alpha_i + \beta' X_{it} + u_{it} + \nu_{it}\,, \tag{4.2}$$

where α_i is the bank-specific effect and output levels, input prices and the time trend are subsumed in the term $\beta' X_{it}$ for simplicity. Here we assume that: (i) $[x_{it}, \nu_{it}, u_{it}]$ are mutually uncorrelated; (ii) α_i is correlated with the regressors X_{it} and (iii) u_{it} is a random draw from a non-negative distribution. We also consider the true random effects model:

$$\ln C_{it} = \alpha + \beta' X_{it} + w_i + u_{it} + \nu_{it}\,, \tag{4.3}$$

where α is the grand mean, w_i is the bank-specific effect and w_i, u_{it} and ν_{it} are mutually uncorrelated and independent of the regressors. Identification in both of these models is achieved through the assumption that inefficiency is time-varying, enabling us to distinguish the bank-specific effect from u_{it}. Given the robustness of our η estimate in the previous section, this appears to be a plausible assumption.

Table 6 compares the results from models 5 and 6 of Table 3 with the estimates when using the estimator for fixed and random effects by Greene (2005).[10]

Looking at the first three columns, which use the same indicator for the price of funding, we can see that there are no significant differences among parameter estimates.[11] Only on the significance of total factor productivity growth do we find mixed results, although not in its sign. From the inefficiency statistics section we can observe that the TRE and TFE models estimate bank-inefficiencies which are lower than model 5, in the first column. This reflects the assumption that time-invariant heterogeneity is different from inefficiency and so, under the absence of fixed effects, estimated inefficiency is smaller than under model 5.

For model 6, shown on the penultimate column, we find the same pattern. In fact, for the TRE estimated with ω_{F3}, the estimated inefficiency distribution is very similar to the estimates for the TRE and TFE models in the second and third columns. Again, median inefficiency values lie below our original estimate.

9. The expressions "true fixed effects" and "true random effects" were coined by Greene (2005) to refer to models where time-invariant heterogeneity is treated separately from inefficiency.

10. The incidental parameter problem raised by Greene (2005) is not a serious issue in this case, as $T = 13$ at the median and $N = 110$. This means that we have enough repeated observations on individuals to estimate individual intercepts.

11. BC92 in the first column is model 5, the baseline from the previous section. BC92 in the penultimate column is model 6.

	Model 5	TRE	TFE	Model 6	TRE
t	-0.02	-0.04***	-0.03	-0.07**	-0.02
	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)
$\ln y_1$	0.62***	0.70***	0.68***	0.47***	0.66***
	(0.07)	(0.05)	(0.07)	(0.09)	(0.05)
$\ln y_2$	0.35***	0.34***	0.29***	0.51***	0.36***
	(0.05)	(0.04)	(0.06)	(0.07)	(0.04)
$\ln \omega_{F2}$	0.56***	0.46***	0.50***		
	(0.10)	(0.09)	(0.11)		
$\ln y_1 \times \ln y_1$	0.07***	0.08***	0.05**	0.09***	0.08***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)
$\ln y_1 \times \ln y_2$	-0.10***	-0.10***	-0.09***	-0.15***	-0.12***
	(0.03)	(0.03)	(0.03)	(0.04)	(0.02)
$\ln y_2 \times \ln y_2$	0.04***	0.05***	0.04***	0.06***	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$\ln \omega_{F3}$				0.40***	0.49***
				(0.09)	(0.08)
μ	0.00			0.62**	
	(0.00)			(0.30)	
η	-0.08***			-0.09***	
	(0.02)			(0.02)	
Obs.	1,243	1,243	1,243	1,243	1,243
Log-likelihood	124.20	194.91	427.79	58.30	135.71
σ_u	0.58	0.16	0.17	0.46	0.18
σ_ν	0.19	0.11	0.09	0.20	0.10
Inefficiency statistics					
Mean	1.74	1.25	1.31	2.26	1.28
Std.dev.	0.69	0.37	0.45	0.98	0.40
25th percentile	1.29	1.05	1.05	1.53	1.04
Median	1.57	1.12	1.15	2.04	1.12
75th percentile	2.08	1.35	1.47	2.82	1.36
Scale economies					
Wald test	0.80	0.27	0.85	0.97	0.46
Scale economies	0.98	1.08	0.98	1.00	1.04

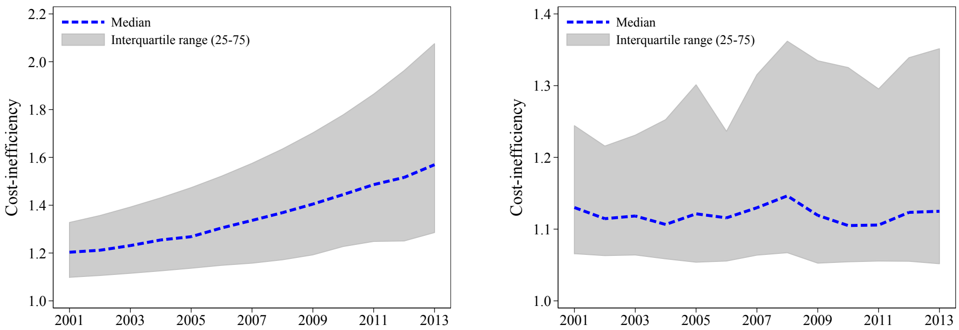
Cluster-robust standard errors in parenthesis
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6. Cost frontier estimates: alternative assumptions

Notes: column titles indicate underlying model and estimator used. BC92: Battese and Coelli (1992) estimator. TRE: true random effects estimator by Greene (2005). TFE: true fixed effects estimator by Greene (2005). The Wald test shows tests' p-values and scale economies are measured at the mean.

Note that both evidence of existence of economies of scope and absence of economies of scale is robust to all specifications, as can be concluded from the statistics presented at the bottom of the table.

Figure 6 displays the evolution of distribution of inefficiency estimates across time for two selected models.



(A) BC92 with $\ln \omega_{F2}$ (B) TRE with $\ln \omega_{F2}$

FIGURE 6: Cost-inefficiency estimates using different models

Given that TFE estimates do not differ substantially from TRE estimates, we conclude that fixed effects are not a significant feature of financial intermediation during this period. Thus, we compare the baseline model (model 5) with the TRE model estimated with ω_{F2}. Note that, as model 5 has a parameterized inefficiency decay factor, η, the level of the distribution increases smoothly through time. The TRE model is semi-parametric, in the sense that estimated inefficiency is allowed to vary freely, which implies that its evolution is much more uneven when compared to model 5 estimates. Note that the median of the TRE model is much more stable across time. This suggests that η, an average, is likely to be heavily influenced by the path of the least efficient banks. If we look at the 75$^{\text{th}}$ percentile of TRE estimates, we can see that these estimates are increasing over time, lending weight to this hypothesis.

An important question then arises: are there significant deviations in bank inefficiency estimates across models? Table 7 contains correlation between a selection of estimated model inefficiencies.

	Model 3	Model 5	Model 6	TRE ω_{F2}	TFE ω_{F2}	TRE ω_{F3}
Model 3	1.00					
Model 5	0.57	1.00				
Model 6	0.50	0.93	1.00			
TRE ω_{F2}	0.29	0.67	0.59	1.00		
TFE ω_{F2}	0.36	0.69	0.59	0.98	1.00	
TRE ω_{F3}	0.27	0.62	0.62	0.93	0.93	1.00

TABLE 7. Correlation between inefficiency measures

Notes: inefficiency estimates from the models on Tables 3 and 6.

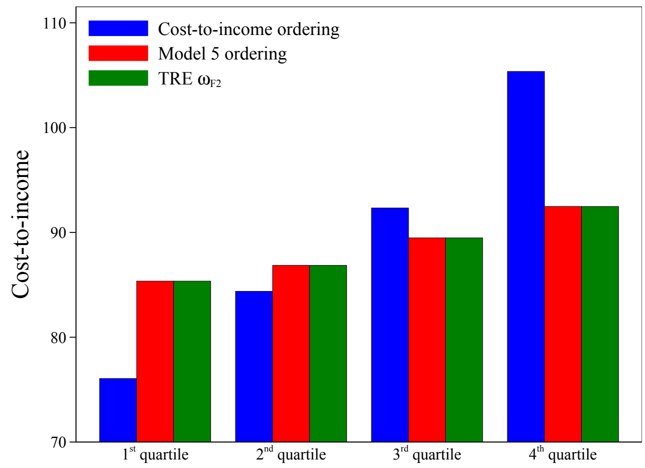


FIGURE 7: Original and model ranking

Notes: banks are ranked according to three inefficiency measures - cost-to-income and the cost-inefficiency estimates from model 5 and TRE ω_{F2}. The figure shows the median cost-to-income by quartile of the three orderings. Costs include interest payments and overheads. Income is interest and other operational income net of provisions/impairments.

Model 3 estimates, which use ω_{F1}, have a comparatively low positive correlation with the models 5 and 6. That correlation drops to around 0.3 when compared to TRE and TFE model estimates.

Interestingly, while the distribution of estimates for model 5 and 6 are somewhat different, their correlation is very high (0.93) lending robustness to estimated bank rankings. Correlation with TRE and TFE models is also elevated even when using ω_{F3}. This also the case between Model 6, TRE and TFE estimates. TRE and TFE models are almost perfectly correlated among themselves, which suggests that both the choice of the price of funding indicator or the assumption on random vs. fixed effects is of little consequence for inefficiency estimates yielded by this framework.

We now have a range of inefficiency estimates which are exogenous with respect to the idiosyncratic risk of an institution. This allows us to rank the cost-to-income indicators based solely on the estimated efficiency of sampled institutions, rather than creating a ranking which is influenced in an unknown direction by risk-taking. Figure 7 shows the differences of this new ranking when compared with the ranking based on cost-to-income.

From this figure we can observe that the new bank ranking yields a cost-to-income distribution with a lower amplitude than the one based on cost-to-income levels. In addition, we observe that modelling random effects separately from inefficiency appears to have very little effect on the sorting of banks, as there is no discernible difference between the quartile medians.

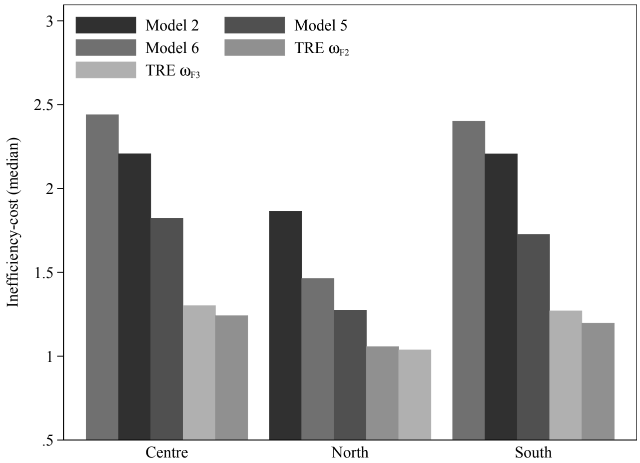


FIGURE 8: Original and model ranking

Notes: bar height shows the (bank) median inefficiency-cost for each region of the EU-15 in 2013, for each model. North: UK, Sweden, Denmark, Ireland, and Finland. Centre: Netherlands, Belgium, Germany, Luxembourg, France, and Austria. South: Portugal, Spain, Italy, and Greece.

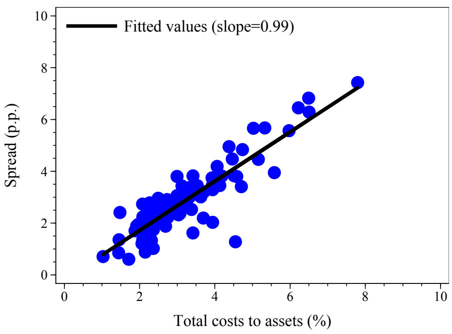
In fact, the differences between the three rankings are much more pronounced in the first and last quartile. This is to be expected, as the banks that are assigned to extreme positions by the cost-to-income sorting are much more likely to be thus ranked for reasons which are unrelated with inefficiency and correlated with risk and exogenous macroeconomic conditions.

Finally, we observe the geographical distribution of bank inefficiency across the EU-15. Figure 8 displays an illustration of this distribution. Clearly, the northern region stands out as the most efficient among the three, while both the Centre and the South are practically indistinguishable in most of the indicators.

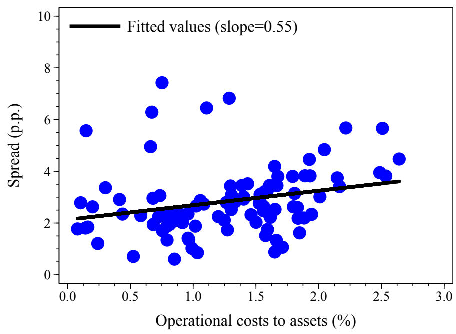
4.3. Inefficiency and credit spreads

From a policy perspective, banks' ability to internally generate own funds may not be the sole reason why bank inefficiency is relevant. If frictions in banking institutions cost/production functions are reflected in credit constraints, their ability to provide credit to the economy may be impaired, amplifying fluctuations. Figure 9 shows how simple and model-based measures are positively correlated with implicit credit spreads.

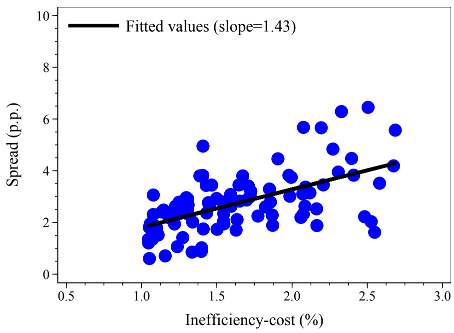
In the first panel, we observe that total costs, a broad measure of inefficiency is positively correlated with the credit spread indicators. However, the inclusion of interest payments for the measurement of inefficiency may inadvertently capture the relationship that was highlighted on section 1, i.e., the positive correlation between risk taking in assets and required return by investors.



(A) Total costs



(B) Operational costs



(C) Inefficiency-cost (Model 5)

FIGURE 9: Credit spreads and inefficiency

Notes: bank-level data for 2013. The spread is the difference between the implicit rate on interest earning assets and the 6-month Euribor.

If we consider operational costs alone, as is done in the second panel of the first row, we find that there is a positive, albeit weaker, correlation. The bottom panel also shows a positive linear relationship between the inefficiency-cost measure of our preferred specification (model 5) and observed bank-level spreads. Given that we already control for the overall level of implicit interest rates on interest paying liabilities on a country-level when computing the inefficiency-cost measure from model 5, it is unlikely that required returns are driving the estimation of a positive coefficient.

To check whether this observation is robust to different indicators of inefficiency, we estimate a linear model of implicit credit spreads with cross-sectional data from 2013.[12] Table 8 contains the results from the exercise.

12. We choose a cross-sectional model instead of a panel data specification because inefficiency estimates for most of the models (with the exception of Greene 2005) change across time at a constant rate, but the ranking remains unaltered.

	(A)	(B)	(C)	(D)	(E)
ω_{F2}	1.05^{***}	0.87^{***}	0.46^{***}	1.05^{***}	0.55^{***}
	(0.20)	(0.13)	(0.17)	(0.12)	(0.11)
HHI	4.50^{**}	5.11^{***}	4.18^{***}	4.54^{***}	4.51^{***}
	(2.08)	(1.63)	(1.38)	(1.29)	(1.48)
Model 2	0.45^{*}				
	(0.24)				
Model 5		1.17^{***}			
		(0.19)			
Model 6			0.93^{***}		
			(0.12)		
TRE ω_{F2}				2.27^{***}	
				(0.50)	
TRE ω_{F3}					2.31^{***}
					(0.22)
Obs.	90	90	90	90	90
R^2	0.37	0.67	0.70	0.73	0.73

Bootstrap standard errors in parenthesis
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8. Spreads and inefficiency under alternative model-based indicators

Notes: Table presents results from OLS estimation of a linear model of spreads as function of inefficiency and other controls. Cost function model names in rows indicate the model from which inefficiency estimates were used in each regression. HHI is the Herfindhal index for credit instituitions' assets at the country level.

Results show a consistently positive association between inefficiency measures and credit spreads. For the measure from model 3, which uses the standard cost of funding indicator, the link between the two is the weakest and the least significant. In contrast, for models 3 and 5, which use country-level cost of funding indicators, the coefficients are larger and more significant. Using the alternative measures, yielded by the models proposed by Greene (2005), the positive and significant association is maintained but roughly doubles in magnitude. Additional controls, ω_2 (median level of implicit interest rate on bank liabilities by country) and the Herfindahl index for credit institution assets (an indicator of concentration of assets in a given member-state), are included to ensure that the estimated positive association does not stem from different levels of bank market power, or from overall risk in a given market.[13] The higher the country median rate on liabilities, the higher the spread on interest-earning assets. In tandem, the higher the Herfindhal index is in a member-state, the higher are the spreads practiced by a bank.

13. Actually, Model 5 and TRE ω_2 are orthogonal to ω_2 by construction.

5. Conclusion

In this paper, we have improved upon traditional cost-to-income as a measure to sort banks on efficiency. To avoid the unknown effects of risk on sorting, we have used total earning assets as part of an outcome measure to fit multiple stochastic frontier models. The advantage of using this variable is that it is a much more stable and predictable component of a bank's accounts and is less likely to be influenced by temporary factors. Additionally, a greater amount of earning assets is likely to be less correlated with risk than income, which is a desirable property. However, this indicator reflects different securitization practices and NPE levels which could influence our inefficiency estimates. This issue is dealt with by applying random intercept estimators to the cost function model. The resulting bank sorting is robust to the utilization of this alternative estimation approach.

Our model-based approach estimates point to a median cost-inefficiency level anywhere between 25 to 100%. These values are highly dependent on the plausibility of the choices one makes on the exogenous cost of funding, which is non-trivial for the shape of the distribution, as well as the particular model. This large uncertainty in what regards the centrality of the distribution of inefficiency is in contrast to the high correlation between inefficiency measures and the very stable ranking between banks generated by our estimates. Regardless of the specification used, we find that there is still a substantial room for improvement for a non-trivial fraction of sampled European banks.

In what concerns the features of the cost function, we find that there exists limited evidence of technological progress in financial intermediation. Economies of scope are an important feature of productivity, while economies of scale remain elusive for the average bank, but there is some evidence of potential savings for the smaller banks in the sample. This finding is important considering that banking system consolidation has been put forward as a solution for banks to return to adequate profitability levels. As we show, it is not clear that these gains exist for the average bank, which implies that this policy may not work in all banking markets. We also find evidence that inefficiency has been increasing over time, likely driven by the set of least efficient institutions.

From a methodological point-of-view, our main contribution is to show that conclusions depend on choice of the indicator for the bank-specific cost of funding. By using country/market level indicators, which are exogenous to individual bank efficiency, we obtain different results and distributions than we do by using the implicit rate on liabilities, which is standard in the literature and we argue to be correlated with inefficiency.

Finally, we uncover a positive association between the computed inefficiency indicators and bank-level implicit credit spreads. This constitutes evidence that bank inefficiency spills over to credit restrictions. This fact should be of interest to policymakers to the extent that it may amplify macroeconomic fluctuations, given that access to credit is subject to frictions in the intermediation production function.

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Anabela Carneiro | Pedro Raposo | Pedro Portugal

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John T. Addison | Pedro Portugal | Hugo Vilares

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Antoine Berthou | Emmanuel Dhyne | Matteo Bugamelli | Ana-Maria Cazacu | Calin-Vlad Demian | Peter Harasztosi | Tibor Lalinsky | Jaanika Meriküll | Filippo Oropallo | Ana Cristina Soares

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João Nicolau | Paulo M. M. Rodrigues

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João Amador | Arne J. Nagengast

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João Amador | Sónia Cabral

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Rita Fradique Lourenço | Paulo M. M. Rodrigues

2016

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Lorenzo Caliendo | Luca David Opromolla | Giordano Mion | Esteban Rossi-Hansberg

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Matei Demetrescu | Paulo M. M. Rodrigues

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Maria M. Campos | Evangelia Papapetrou | Domenico Depalo Javier J. Pérez | Roberto Ramos

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Diana Bonfim | Gil Nogueira | Steven Ongena

8|16 The effect of quantitative easing on lending conditions
Laura Blattner | Luísa Farinha | Gil Nogueira

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João Pedro Pereira | Vasco Pesquita | Paulo M. M. Rodrigues | António Rua

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N. Bokan | A. Gerali | S. Gomes | P. Jacquinot | M. Pisani

11|16 Temporary contracts' transitions: the role of training and institutions
Sara Serra

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António Rua

13|16 Forecasting banking crises with dynamic panel probit models
António Antunes | Diana Bonfim | Nuno Monteiro | Paulo M. M. Rodrigues

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Daniel A. Dias | Carlos Robalo Marques | Christine Richmond

15|16 The unsecured interbank money market: a description of the Portuguese case
Sofia Saldanha

16|16 Leverage and risk weighted capital requirements
Leonardo Gambacorta | Sudipto Karmakar

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Nuno Alves | Diana Bonfim | Carla Soares

18|16 Public debt expansions and the dynamics of the household borrowing constraint
António Antunes | Valerio Ercolani

2017

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Giordano Mion | Luca David Opromolla | Alessandro Sforza

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Paulo Guimarães | Fernando Martins | Pedro Portugal

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Pedro Portugal | António Rua

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Sónia Félix | Pedro Portugal

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Diana Bonfim | Sónia Costa

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Luís Martins | Manuel Coutinho Pereira

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Luciana Barbosa

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Cristina Manteu | Sara Serra

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António Rua

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Olivier Blanchard | Pedro Portugal

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João Oliveira