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Pricing inputs and outputs in banking: an application to CEE countries

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Abstract:

Aim: A problem in efficiency and productivity studies in banking is that some of the input and output prices used in the estimation of cost, revenue and profit functions are proxies of questionable quality with obvious impact on the reliability of performance measures. We address this issue focussing on the banking systems of Central and Eastern Europe where arguable this problem may even be more acute.

Design / Research methods: We employ parametric forms of directional distance functions to obtain shadow prices of bank inputs and outputs, and compare them with price proxies typically employed in empirical studies. The key idea here is to exploit cost, revenue and profit maximisation as the optimisation criteria to derive pricing rules, which allow us to find shadow prices for both inputs and outputs. We show how knowledge of one input price can be used to price outputs and how knowledge of one output price can be used to price inputs along with information on input and output quantities. We also use total cost to shadow price inputs and total revenue to shadow price outputs.

Conclusions / findings: We find differences between shadow prices and actual prices suggesting that input and/or output mix may not be consistent with cost minimisation or revenue and profit maximisation. We also find that bank efficiency is highest on average in Estonia, which also boasts the highest bank capitalisation rate in the CEE region.

Originality / value of the article: The study departs from the traditional literature on efficiency and productivity by focussing on pricing and their implications thereof for input-output mix.

Implications of the research: Prices for problem loans are not observable, hence our approach provides an avenue for computing shadow prices for bad outputs in banking. This is important since it gives us an indication of the loss of good output needed to lower the bad output by one unit.
Key words: directional distance function, bank efficiency, shadow prices, CEE banking
JEL: D24, G21, C61

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1. Introduction

A well-known problem in efficiency and productivity studies in banking is that some of the input and output prices used in the estimation of cost, revenue and profit functions are proxies of questionable quality. The implications of this problem can be wide ranging, not only influencing directly bank performance measures, but may also be affecting, among others, measures of returns to scale, as well as merger and acquisitions decisions, credit risk assessments, and the measurement of financial services with direct links to deposits and loans or other financial products in the national accounts. Arguably, the problem is even more acute in the case of banking systems in developing countries. Our focus are the banking systems of Central and Eastern Europe (CEE).[1] We employ parametric forms of directional distance functions to obtain shadow prices of bank inputs and outputs, and contrast them with price proxies typically employed in empirical studies. We pay particular attention to the modelling of both good and bad outputs recognising the importance of credit risk for banks.

We exploit cost minimisation and revenue maximisation as the optimisation criteria to derive direct pricing rules, which allow us to find shadow prices for both inputs and outputs. We show how knowledge of bank cost can be used to price inputs and knowledge of bank revenue can be used to price outputs along with information on input and output quantities. We also obtain indirect or crossover pricing rules exploiting profit maximisation as the optimisation criterion, which allows us to find shadow prices for both inputs and outputs simultaneously. We show how knowledge of one input price can be used to price outputs and how knowledge of one output price can be used to price inputs along with information on input and output quantities. We parameterise the directional input distance function using a quadratic functional form. We then proceed to obtain shadow prices for inputs utilising an input directional distance function, shadow prices for outputs

[1] Studies with a focus on CEE banking efficiency and productivity include Fries and Taci (2005), Koutsomanoli-Filippaki et al. (2009a, b), Yildirim and Philippatos (2007).

using an output directional distance, and price inputs and outputs simultaneously utilising a directional distance function with both input and output orientation.

We study seven CEE banking systems, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland and Slovakia. Our focus is the post financial and sovereign crisis period, specifically the four-year period 2013-2016. While different in many respects, the banking systems of the CEE countries are characterised by high market concentration, ranging from well in excess of 70 percent in Estonia and Latvia to a low of around 45% in Poland, and high foreign (mainly Western European) ownership, in particular in the Czech Republic, Estonia, Lithuania and Slovakia. Both high rates of concentration and foreign ownership are the result of market deregulation and economic reform in conjunction with the countries accession to the European Union. The CEE countries and their banking systems attained high growth rates driven by large foreign capital inflows in the period prior to the financial crisis. While not directly involved in the menace of toxic assets, the crises did have adverse effects albeit at varying degrees on CEE bank portfolios with large declines in profitability driven by the very high level of impairment costs (Deloitte, 2012). The Czech, Polish and Slovak banking sectors managed to get through the crisis much more easily than those of the Baltic States and Hungary did.

However, one concern was that many of these countries, especially the three Baltic States expanded far too much in the immediate period preceding the global financial crisis, and hence became very vulnerable to major external shocks recognising that much of the expansion was triggered by foreign capital inflows. The upshot of this was that total bank assets fell quite rapidly in the three Baltic States between 2007 and 2012, with Estonia recording the largest drop in banking assets (in excess of 40 percent) during this period according to figures compiled by Eurostat. In contrast, the Czech Republic and especially Poland recorded large increases in total banking assets during the same period. Banking assets as a percentage of GDP fell by almost half in the case of Estonia, from over 220 percent to about 120 percent, and by about one quarter, from about 100 percent to 70 percent in Lithuania and from about 160 percent to just over 120 percent in Latvia. The Czech Republic recorded a modest increase, with total banking assets rising from about 105 percent of GDP to 115 percent, while in Poland they increased from about

70 percent to 85 percent of GDP. Clearly, Estonia was way overleveraged in the years before the crisis, and the substantial drop in leverage indicates a much needed rationalisation of its banking sector, bringing Estonia and to a lesser extent Latvia more in sync with the other CEE countries.

A second concern was that the development of the banking sectors of the CEE countries following accession to the European Union was driven by asset expansion with very little evidence of relative prices for inputs and outputs adjusting to reflect the opportunities for rationalisation made available through financial market deregulation and more widely through the overall economic reform programme. This is important, especially in view of major developments in the post crisis period associated with stricter regulatory requirements.

The paper is organised as follows. Section 2 describes the methodology used to compute the efficiency measures and shadow prices for inputs and outputs. Section 3 describes the data and presents the empirical results. Section 4 concludes the paper.

2. Methodology

2.1. Parametric method

The parametric method uses a functional form to model empirically the associated distance function, from which the shadow prices of outputs can be calculated. Once the functional form is determined, we use linear programming to estimate the parameters of the model. Aigner and Chu (1968) proposed a deterministic linear programming model for calculating the parameters of the distance function. This model has been widely employed in shadow price estimation. Its objective is to seek a set of parameters that minimises the sum of deviations of the distance function value from the frontier of production technology subject to the underlying technology constraints. The constraint conditions cover the feasibility, monotonicity, disposability, translation properties of the distance function. While desirable inputs and outputs satisfy strong disposability, we assume that undesirable outputs (non-performing loans) and desirable outputs satisfy only joint weak disposability. In addition, we require that the functional form should be flexible, i.e. allow for interaction and second order terms to provide a complete characterisation of technology. Färe and Sung (1986) show that within the class of generalised quadratic functions, the quadratic function is the best choice for the directional distance function, in the sense that provides a second order approximation to the true but unknown production relation, with parameters restrictions to satisfy the translation property.

We assume that we observe inputs, good and bad output data, $(x, y, b) \in \mathbb{R}^N_{\geq} \times \mathbb{R}^M_{\geq} \times \mathbb{R}^J_{\geq}$ and in addition, we assume that both input and output direction vectors $g^x = (g^x_1, \dots, g^x_N), g^y = (g^y_1, \dots, g^y_M), g^b = (g^b_1, \dots, g^b_J)$ have been chosen. We estimate the directional technology distance function $\vec{D}_T((x, y, b; g^x, g^y, g^b)$ using a quadratic functional form. We recall that the direct representation of directional technology distance function is defined as

$$\vec{D}_T(x, y, b; g^x, g^y, g^b) = max\,\{\beta : (x - \beta g^x, y + \beta g^y, b - \beta g^b) \in T\}$$

Note that this function satisfies the representation and translation properties, i.e,

$$T = \{(x, y, b) : \vec{D}_T(x, y, b; g^x, g^y, g^b) \geq 0\},$$
$$\vec{D}_T(x - \alpha g^x, y + \alpha g^y, b - \beta g^b; g^x, g^y, g^b)$$
$$= \vec{D}_T(x, y, b; g^x, g^y, g^b) - \alpha, \quad \alpha \in \mathbb{R}.$$

To translate the shadow pricing formulas into empirical results we need to parameterize the distance function. We choose the quadratic functional form expressed by:

$$\vec{D}_T(x, y, b; g^x, g^y, g^b) = \alpha_0 + \sum_{n=1}^{N} \alpha_n x_n + \sum_{m=1}^{M} \beta_m y_m + \sum_{j=1}^{J} \gamma_j b_j$$
$$+ \frac{1}{2}\sum_{n=1}^{N}\sum_{n'=1}^{N} \alpha_{nn'} x_n x_{n'} + \frac{1}{2}\sum_{m=1}^{M}\sum_{m'=1}^{M} \beta_{mm'} y_m y_{m'} + \frac{1}{2}\sum_{j=1}^{J}\sum_{j'=1}^{J} \gamma_{jj'} b_j b_{j'}$$
$$+ \sum_{n=1}^{N}\sum_{m=1}^{M} \delta_{nm} x_n y_m + \sum_{n=1}^{N}\sum_{j=1}^{J} \nu_{nj} x_n b_j + \sum_{m=1}^{M}\sum_{j=1}^{J} \mu_{mj} y_m b_j$$

s.t.

$$\alpha_{nn'} = \alpha_{n'n}, n \neq \acute{n};\ \beta_{mm'} = \beta_{m'm}, m \neq m';\ \gamma_{jj'} = \gamma_{j'j}, j \neq j'.$$

We estimate the quadratic directional distance function using linear programming methods following Aigner and Chu (1968) by solving the following linear programming problem:

$$\min \sum_{k=1}^{n} \vec{D}_T(x^k, y^k, b^k; g^x, g^y, g^b)$$

$s.t.$

$$(1)\ \vec{D}_T(x^k, y^k, b^k; g^x, g^y, g^b) \geq 0, \qquad k = 1, \ldots, K, \quad (feasibility)$$

$$(2)\ \partial_{y_m} \vec{D}_T(x^k, y^k, b^k; g^x, g^y, g^b) \leq 0, k = 1, \ldots, K, \quad m = 1, \ldots, M, \quad (monotonicity)$$

$$(3)\ \partial_{x_n} \vec{D}_T(x^k, y^k, b^k; g^x, g^y, g^b) \geq 0, k = 1, \ldots, K, \quad n = 1, \ldots, N, \quad (monotonicity)$$

$$(4)\ \partial_{b_j} \vec{D}_T(x^k, y^k, b^k; g^x, g^y, g^b) \geq 0, k = 1, \ldots, K, \quad j = 1, \ldots, J, \quad (monotonicity)$$

$$(5) - \sum_{n=1}^{N} \alpha_n g_n^x + \sum_{m=1}^{M} \beta_m g_m^y - \sum_{j=1}^{J} \gamma_j g_j^b = -1, \qquad (translation),$$

$$- \sum_{n=1}^{N} \delta_{nm} g_n^x + \sum_{\acute{m}=1}^{M} \beta_{mm'} g_m^y - \sum_{j=1}^{J} \mu_{mj} g_j^b = 0, \qquad \mathrm{m} = 1, \ldots, \mathrm{M},$$

$$- \sum_{n=1}^{N} \nu_{nj} g_n^x + \sum_{m=1}^{M} \mu_{mj} g_m^y - \sum_{j=1}^{J} \gamma_{jj} g_j^b = 0, \qquad j = 1, \ldots, J,$$

$$- \sum_{n'=1}^{N} \alpha_{n\acute{n}} g_n^x + \sum_{\mathrm{m}=1}^{M} \delta_{nm} g_m^y - \sum_{j=1}^{J} \nu_{nj} g_j^b = 0, \qquad \mathrm{n} = 1, \ldots, \mathrm{N},$$

$$(6)\ \alpha_{nn'} = \alpha_{n'n}, n \neq \acute{n};\ \beta_{mm'} = \beta_{m'm}, m \neq m';\ \gamma_{jj'} = \gamma_{j'j}, j \neq j'. (Symmetry)$$

Noting that

$$\partial_{x_n} D_T(x^k, y^k, b^k) = \frac{\partial D_T(x,y,b)}{\partial x_n}$$
$$= \alpha_n + \sum_{n'=1}^{N} \alpha_{nn'} x_{n'}^k + \sum_{m=1}^{M} \delta_{nm} y_m^k + \sum_{j=1}^{J} v_{nj} b_j^k,$$

$$\partial_{y_m} D_T(x^k, y^k, b^k) = \frac{\partial D_T(x,y,b)}{\partial y_m}$$
$$= \beta_m + \sum_{m'=1}^{M} \beta_{mm'} y_{m'}^k + \sum_{n=1}^{N} \delta_{nm} x_n^k + \sum_{j=1}^{J} \mu_{mj} b_j^k,$$

$$\partial_{b_j} D_T(x^k, y^k, b^k) = \frac{\partial D_T(x,y,b)}{\partial b_j}$$
$$= \gamma_j + \sum_{j'=1}^{J} \gamma_{jj'} b_{j'}^k + \sum_{n=1}^{N} v_{nj} x_n^k + \sum_{m=1}^{M} \mu_{mj} y_m^k.$$

We use the same functional form for all banks, large and small and across different CEE banking systems, recognising that all banks face fundamentally the same production technology for traditional core banking activities (i.e., taking deposits and making loans). Although the largest banks may rely a lot more on securities trading and off-balance-sheet activities, it is not a priori clear whether this will impact significantly on the empirical results recognising that the CEE region is dominated by banks with largely a traditional focus.[2]

2.2. Pricing models and shadow prices

We follow the approach of Färe et al. (2017) to obtain shadow prices using the estimated distance functions via the Lagrangian method. We use different pricing rules based on different, in terms of their orientation, directional distance functions associated with different optimisation criteria. The pricing rule based on an input directional distance function is associated with cost minimisation as the behavioural

[2] Spierdijka et al. (2017) present a similar argument for the US bank market, characterised by a small number of very large banks and a very large number of smaller banks.

criterion and requires either total cost or one of the input prices to be observed. The pricing rule based on an output directional distance function is associated with revenue maximisation as the behavioural criterion and requires either total revenue or one of the output prices to be known. The pricing rule based on a directional distance function with both input and output orientation is associated with profit maximisation and requires one of the input or output prices to be known. When we require one of the prices to be known, we rely on what we perceive to be the most reliable input or output price proxy to calculate shadow prices for the other inputs and outputs. For robustness purposes, we experiment with alternative choices of the 'known' price. We then compare the shadow prices with actual prices. Since we are also interested in pricing bad outputs (non-performing loans and leases), we obtain shadow prices of the bad output and compare it with the actual and shadow price of the corresponding good output (loans and leases).

We first show how to calculate shadow prices for inputs and outputs using a directional distance function. We rely on profit maximisation as the optimisation criterion, which allows us to construct shadow prices for both inputs and outputs simultaneously. Second, we construct input prices using an input directional distance function. Third, we exploit revenue maximisation as the optimisation criterion to construct shadow prices for outputs, both desirable and undesirable. To do this we use the output directional distance function.

In an environment of low interest rates coupled with important regulatory changes, we would expect that bank revenues from interest-bearing activities be under pressure thereby directly affecting bank profitability (see Spierdijka et al., 2017). Under these conditions, cost management by banks in terms of their ability to use inputs more efficiently, not only in a technical efficiency sense but also in terms of their ability to respond efficiently to changing relative prices is important. To this end, we set out to calculate shadow input and output prices representing the opportunity cost of choosing the observed input or output quantity (i.e. the opportunity cost of money to the bank from the perspective of the next best alternative use). We compare these prices with the actual observed (proxy) prices of inputs and outputs. In particular, we focus on prices for deposits, loans, other earnings assets and loan loss provisions. Since smaller banks may have lesser ability to diversify their activities, we would like to see if there any differences between large and small banks. We also assess performance in relation to a host of indicators related to funding structure, liquidity and asset structure.

We set up the profit maximisation Lagrangian problem as follows

$$\max py - wx - rb - \mu \vec{D}_T(x, y, b; g^x, g^y, g^b)$$

where p, w, r are the prices for desirable outputs y , inputs (x), and undesirable outputs (b), respectively, and μ is the Lagrangian multiplier (e.g. a measure of how much profit would increase if the optimisation constraint was relaxed). The first order conditions associated with the Lagrangian profit maximization problem are as follows:

$$p - \mu \nabla_y \vec{D}_T(x, y, b; g^x, g^y, g^b) = 0,$$
$$-w - \mu \nabla_x \vec{D}_T(x, y, b; g^x, g^y, g^b) = 0$$
$$-r - \mu \nabla_b \vec{D}_T(x, y, b; g^x, g^y, g^b) = 0$$

If one output price, say p_1, is known then we have

$$\mu = \frac{p_1}{\partial_{y_1} \vec{D}_T(x, y, b; g^x, g^y, g^b)}$$

which as shown by Färe et al. (2017) yields the estimation of all other prices, $w_1, \dots, w_m, p_2, \dots, p_s$ as:

$$(w_1, \dots, w_N) = -\frac{p_1}{\partial_{y_1} \vec{D}_T(x, y, b; g^y, g^b)} \left(\partial_{x_1} \vec{D}_T(x, y, b; g^x g^y, g^b), \dots, \partial_{x_N} \vec{D}_T(x, y, b; g^x, g^y, g^b)\right),$$

$$(p_2, \dots, p_M) = \frac{p_1}{\partial_{y_1} \vec{D}_T(x, y, b; g^y, g^b)} \left(\partial_{y_2} \vec{D}_T(x, y, b; g^x g^y, g^b), \dots, \partial_{y_M} \vec{D}_T(x, y, b; g^x g^y, g^b)\right),$$

$$(r_1, \dots, r_J) = \frac{p_1}{\partial_{y_1} \vec{D}_T(x, y, b; g^y, g^b)} \left(\partial_{b_1} \vec{D}_T(x, y, b; g^x g^y, g^b), \dots, \partial_{b_J} \vec{D}_T(x, y, b; g^x g^y, g^b)\right),$$

Similarly, if one of the input prices, say w_1, is known then

$$\mu = -\frac{w_1}{\partial_{x_1}\vec{D}_T(x, y, b; g^x g^y, g^b)}$$

which yields the estimation of all other prices, $w_1, \dots, w_m, p_2, \dots, p_s$ as:

$$(w_1, \dots, w_N) = \frac{w_1}{\partial_{x_1}\vec{D}_T(x, y, b; g^x g^y, g^b)}\left(\partial_{x_2}\vec{D}_T(x, y, b; g^x g^y, g^b), \dots, \partial_{x_N}\vec{D}_T(x, y, b; g^x g^y, g^b)\right),$$

$$(p_1, \dots, p_M) = -\frac{w_1}{\partial_{x_1}\vec{D}_T(x, y, b; g^x g^y, g^b)}\left(\partial_{y_1}\vec{D}_T(x, y, b; g^x g^y, g^b), \dots, \partial_{y_M}\vec{D}_T(x, y, b; g^x g^y, g^b)\right),$$

$$(r_1, \dots, r_J) = \frac{w_1}{\partial_{x_1}\vec{D}_T(x, y, b; g^x g^y, g^b)}\left(\partial_{b_1}\vec{D}_T(x, y, b; g^x g^y, g^b), \dots, \partial_{b_J}\vec{D}_T(x, y, b; g^x g^y, g^b)\right)$$

From here, by altering the optimisation criterion and rewriting the first order conditions for cost minimization in lieu of profit maximisation, viz.

$$-w - \mu \nabla_x D_I(x, y, b; g^x) = 0,$$

we can derive the input pricing rule as

$$(w_1, \dots, w_N) = C\,\frac{\left(\partial_{x_1} D_I(x, y, b; g^x), \dots, \partial_{x_N} D_I(x, y, b; g^x)\right)}{\partial_x D_I(x, y, b; g^x).x},$$

where C is observed total cost. Similarly, applying the first order conditions for revenue maximisation,

$$p - \mu \nabla_y D_O(x, y, b; g^y, g^b) = 0 \text{ and } -r - \mu \nabla_b D_O(x, y, b; g^y, g^b) = 0,$$

we can obtain pricing rules for desirable and undesirable outputs as:

$$(p_1, \dots, p_M) = R\,\frac{\left(\partial_{y_1} D_O(x, y, b; g^y, g^b), \dots, \partial_{y_M} D_O(x, y, b; g^y, g^b)\right)}{\partial_y D_O(x, y, b; g^y, g^b).y},$$

$$(r_1, \dots, r_J) = R\,\frac{\left(\partial_{b_1} D_O(x, y, b; g^y, g^b), \dots, \partial_{b_J} D_O(x, y, b; g^y, g^b)\right),}{\partial_y D_O(x, y, b; g^y, g^b).y}$$

where R is observed total revenue.

3. Empirical application

We use data obtained from Orbis Bank Focus over the period 2013 to 2016. We follow the intermediation approach (see Sealey and Lindley, 1977). We assume banks use a production technology consisting of three inputs, labour measured by staff costs, capital measured by fixed assets and deposits; two desirable outputs, loans and other earning assets, and one undesirable output (loan loss reserves). We measure the price of deposits as the ratio of interest paid on deposits over total deposits, the price of loans as interest income on loans over total loans, and the price of other earning assets as interest income on other earning assets over other earning assets.

Table 1 presents the descriptive statistics of the data as well as the efficiency measures. Poland is the largest banking sector in the CEE. Funding costs (deposit prices) are on average lowest in the Baltic States while interest rate margins (difference between loan and deposit prices) are largest in Hungary and Poland.

Table 1. Descriptive Statistics

	Variables		CZ	EE	HU	LT	LV	PL	SK
			Mean (Std. Dev)						
Inputs-Outputs	Inputs	SE	59,918	10,541	101,607	21,785	23,209	127,211	48,851
			(92,351)	(12,139)	(167,030)	(16,773)	(19,532)	(152,463)	(46,304)
		CD	5,569,586	737,368	4,663,658	2,214,214	1,813,112	8,411,963	3,700,694
			(7,972,065)	(1,148,849)	(6,479,863)	(2,173,354)	(1,886,960)	(10,693,660)	(3,488,906)
		FA	60,200	3,533	107,099	15,806	25,188	89,099	48,152
			(119,960)	(3,109)	(185,962)	(20,497)	(19,729)	(139,359)	(55,241)
	desired outputs	L	4,837,779	847,501	3,601,175	1,982,595	1,232,896	8,137,381	3,367,852
			(6,184,529)	(1,476,762)	(4,822,613)	(1,962,016)	(1,729,883)	(10,064,639)	(3,368,447)
		OEA	2,597,441	167,928	2,218,984	511,340	736,813	3,081,602	1,260,703
			(4,182,332)	(233,744)	(2,452,269)	(451,863)	(759,078)	(3,559,381)	(1,254,961)
	Undesired output	LLR	162,681	16,596	598,424	45,199	50,546	386,009	135,485
			(202,480)	(20,454)	(939,564)	(46,347)	(49,888)	(458,911)	(120,123)
Prices		P(D)	0.0108	0.0076	0.0188	0.0056	0.0049	0.0185	0.0117
			(0.0101)	(0.0098)	(0.0135)	(0.0049)	(0.0048)	(0.0093)	(0.0072)
		P(L)	0.0491	0.0348	0.0666	0.0392	0.0546	0.0535	0.0509
			(0.0214)	(0.0129)	(0.0215)	(0.0211)	(0.0213)	(0.0217)	(0.0162)
		P(OEA)	0.0226	0.0583	0.0507	0.0202	0.0134	0.0375	0.0269
			(0.0177)	(0.1775)	(0.0273)	(0.0102)	(0.0094)	(0.0217)	(0.0085)
Efficiencies		DI	0.8400	0.9189	0.6852	0.8539	0.8175	0.7450	0.7434
			(0.1706)	(0.0762)	(0.2084)	(0.0125)	(0.1146)	(0.2040)	(0.1740)
		DO	0.8623	0.9276	0.6483	0.8902	0.8813	0.7951	0.8183
			(0.1288)	(0.0393)	(0.82249)	(0.8902)	(0.0742)	(0.1701)	(0.0930)
		DT	0.8981	0.9437	0.7456	0.9046	0.8886	0.8259	0.0.8321
			(0.1139)	(0.0397)	(0.1938)	(0.0819)	(0.0745)	(0.1542)	(0.1113)
	# Observations		90	24	49	20	57	97	45

Notes: SE is staff expenses, CD is customer deposits measured in thousands of Euros, FA is fixed assets measured in thousands of Euros, L is loans measured in thousands of Euros, OEA is other earnings assets measured in thousands of Euros, NPL is reserves for non-performing-loans. DI, DO and DT are the efficiency scores based an input directional distance function, output directional distance function, and a directional distance function with both input and output orientation, respectively. For convenience, efficiency scores are reported in the range of zero to one, by rescaling the distance function (DDF) values as 1/(1+DDF). Figures in brackets denote standard deviations. CZ=Czech Republic, EE= Estonia, HU=Hungary, LT=Lithuania, LV=Latvia, PL=Poland and SK= Slovakia.

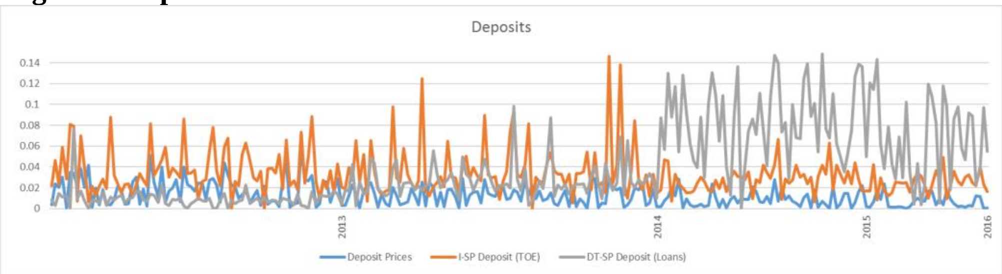
3.1 Empirical results

We estimate directional distance functions by setting the values of the directional vector equal to the data averages. More specifically, we set $g^x = \vec{x}, g^y = 0, g^b = 0$ for the input directional distance function, $g^x = 0, g^y = \vec{y}, g^b = \vec{b}$ for the output directional distance function, and $g^x = \vec{x}, g^y = \vec{y}, g^b = \vec{b}$ for the directional distance function with both input and output orientation. To estimate the constrained optimisation model given by (1)-(6), we first normalise each output and input by its mean value. This has the convenience of ease of interpretation of the parameter estimates of the directional distance function (see Färe et al., 2001 and Cuesta and Zofio, 2005). Using data averages as the direction also has the convenience of estimating the normalised model with direction values equal to unity. However, when we calculate shadow prices, we adjust the gradients to conform to the pricing rules given above.

Table 1 shows efficiency is highest in Estonia where there has been considerable rationalisation of the banking system, and lowest in Hungary where profitability has been under pressure, in part because of government-imposed levies albeit mainly because of the economy's vulnerability to external financial shocks. As to be expected, efficiency scores from the directional distance function (DT) are greater than those obtained by the partial orientation models (DI and DO), since DT allows banks to adjust both inputs and outputs simultaneously.

Figures 1-4 plot actual prices and shadow prices for all banks during the entire sample period 2013-2016. Figure 1 shows the actual price of deposits and the shadow prices calculated from the input directional distance function (DI) using information on total cost (I-SP Deposits) and the directional distance function (DT) using the crossover pricing rule with information on the price of loans (DT-SP Deposits). Our estimates show that the opportunity cost rate of deposits is generally greater than the actual interest rate paid on deposits, and this gap has increased in the latter part of the sample period. In a simplified situation where there is infinite supply of deposits, the shadow price would presumably be zero. Hence, a positive value is indicative of the intrinsic cost to the bank to ramp deposits up or down quickly in order to meet liquidity demands or regulatory requirements.

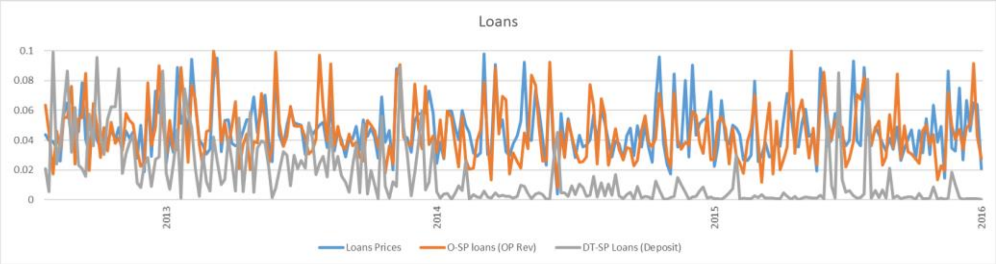
Figure 1. Deposits Prices



Notes: I-SP Deposits (TOE) indicates that the shadow price for deposits is calculated from an input directional distance function with known total expenses (TOE); DT-SP Deposits (Loans) indicates that the shadow price for deposits is calculated from a directional distance function using a crossover pricing rule with known price of loans.

Figure 2 shows the actual and shadow prices of loans calculated from the output directional distance function (DO) using information on total revenue (O-SP Loans) and the directional distance function (DT) using the crossover pricing rule with information on the price of deposits (DT-SP Loans). Our estimates show that the opportunity cost rate of loans (O-SP) is generally similar to the actual price of loans while the alternative measure (DT-SP) indicates a lower opportunity cost.

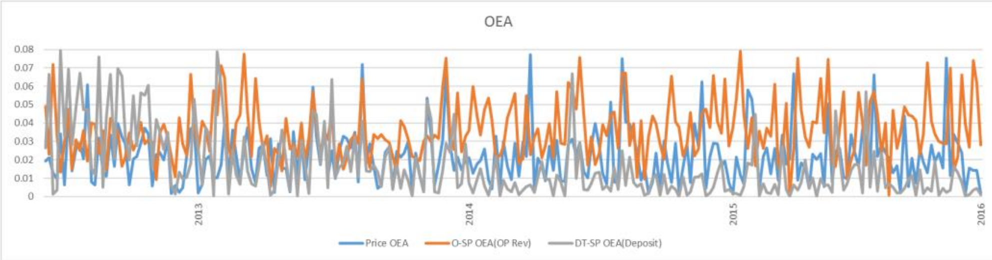
Figure 2. Loan Prices



Notes: O-SP loans (OP Rev) indicates that the shadow price for loans is calculated from an output directional distance function with known operating revenue (OP Rev); DT-SP loans (Deposits) indicates that the shadow price for loans is calculated from a directional distance function using a crossover pricing rule with known price of deposits.

Figure 3 displays the actual price of other earning assets and its shadow price calculated from the output directional distance function (DO) using information on total revenue (O-SP OEA) and the directional distance function (DT) using the crossover pricing rule with information on the price of deposits (DT-SP OEA). Our estimates show that the opportunity cost rate of other earning assets (O-SP OEA) is generally greater than the actual price but lower when calculated from the directional distance function. We ascribe these differences to the differences in the construction of pricing rules (direct versus crossover) and differences in the optimisation criteria (revenue versus profit maximisation).

Figure 3. Other Earning Assets Prices

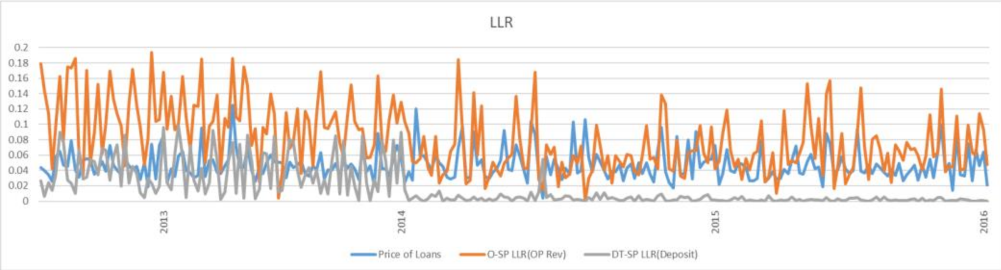


Notes: O-SP OEA (OP Rev) indicates that the shadow price for other earning assets (OEA) is calculated from an output directional distance function with known operating revenue (OP Rev); DT-SP (Deposits) indicates that the shadow price for OEA is calculated from a directional distance function using a crossover pricing rule with known price of deposits.

Figure 4 shows the actual price of loans and the shadow price of loan loss reserves calculated from the output directional distance function (DO) using information on total revenue (O-SP LLR) and the directional distance function (DT) using the crossover pricing rule with information on the price of deposits (DT-SP LLR). Bad output prices are not observable, hence shadow prices provide useful information in assessing the opportunity cost of reducing the bad output by one unit. Our estimates show that the opportunity cost of loan loss reserves (O-SP LLR) is generally greater than the actual price of loans; however, it is lower when calculated from the directional distance function. Since these opportunity costs relate to loss of revenue (gross income) vis-a-vis loss of profit (net income), such differences may not be entirely surprising.

We turn next to gain more insights on our bank performance measures by relating them to various indicators of size, liquidity, revenue sustainability, asset and funding structure as shown in the tables below. Table 2 displays efficiency averages and price ratio averages across different bank sizes measured by total assets. We find that smaller banks are more efficient whereas larger banks are the least efficient. Concerning price ratios, the most notable patterns arise in relation to the ratio of the shadow price of LLR to the price of loans, and the ratio of shadow prices of loans to deposits.

Figure 4. Loan Loss Reserve Shadow Prices



Notes: O-SP LLR (OP Rev) indicates that the shadow price for loan loss reserves (LLR) is calculated from an output directional distance function with known operating revenue (OP Rev); DT-SP LLR (Deposits) indicates that the shadow price for LLR is calculated from a directional distance function using a crossover pricing rule with known price of deposits.

Table 2. Efficiency and Relative Prices across different bank sizes

TA		eff_{DT}	eff_{DI}	eff_{DO}	$\frac{S(L)}{P(L)}$	$\frac{S(D)}{P(D)}$	$\frac{S(LLR)}{P(L)}$	$\frac{P(L)}{P(D)}$	$\frac{S(L)}{S(D)}$	$\frac{P(L)}{P(OEA)}$	$\frac{S(L)}{S(OEA)}$
Small		0.9450	0.9254	0.9156	0.9922	1.0297	1.0636	1.0430	0.9883	1.0267	0.9981
		(0.0419)	(0.0660)	(0.0421)	(0.0380)	(0.0290)	(0.0622)	(0.0301)	(0.1065)	(0.0616)	(0.0270)
Medium		0.8664	0.8071	0.8228	0.9913	1.0177	1.0406	1.0356	1.0003	1.0330	1.0061
		(0.0972)	(0.1125)	(0.1285)	(0.0183)	(0.0981)	(0.0434)	(0.0962)	(0.0729)	(0.0351)	(0.0202)
Large		0.7520	0.6298	0.7254	1.0074	1.0239	1.0240	1.0343	1.0136	1.0140	1.0148
		(0.1686)	(0.1976)	(0.2011)	(0.0177)	(0.0195)	(0.0475)	(0.0150)	(0.0399)	(0.0162)	(0.0364)

Notes: TA, L, D, OEA, LLR are total assets, loans, customer deposits, other earning assets and loan loss reserves, respectively. P and S stands for price and shadow price, e.g. S(L) is the shadow price for loans.

The loans to deposits ratio (L/D) shows how lending activity is matched to the expansion of the deposits base. Table 3 shows that banks with lower L/D ratios are more efficient. Again no clear patterns arise in relation to most price ratios aside from the actual and shadow price ratios of loans to deposits.

Table 3. Efficiency and Relative Prices across loan to deposits ratio

L/D		eff_{DT}	eff_{DI}	eff_{DO}	$\frac{S(L)}{P(L)}$	$\frac{S(D)}{P(D)}$	$\frac{S(LLR)}{P(L)}$	$\frac{P(L)}{P(D)}$	$\frac{S(L)}{S(D)}$	$\frac{P(L)}{P(OEA)}$	$\frac{S(L)}{S(OEA)}$
Small		0.9105	0.8536	0.8807	0.9971	1.0186	1.0500	1.0514	1.0274	1.0385	1.0118
		(0.1003)	(0.1526)	(0.1108)	(0.0329)	(0.0205)	(0.0630)	(0.0247)	(0.0250)	(0.0286)	(0.0304)
Medium		0.8042	0.7068	0.7653	1.0021	1.0186	1.0287	1.0343	1.0166	1.0164	1.0132
		(0.1493)	(0.1800)	(0.1687)	(0.0166)	(0.0195)	(0.0444)	(0.0142)	(0.0178)	(0.0191)	(0.0218)
Large		0.8480	0.8004	0.8170	0.9919	1.0343	1.0482	1.0264	0.9585	1.0182	0.9942
		(0.1437)	(0.1847)	(0.1722)	(0.0286)	(0.1042)	(0.0500)	(0.1002)	(0.1214)	(0.0627)	(0.0313)

Notes: L, D, OEA, LLR are loans, customer deposits, other earning assets and loan loss reserves, respectively. P and S stands for price and shadow price, e.g. S(L) is the shadow price for loans.

Other earning assets to total assets ratio (OEA/TA) provides information on asset structure, and more generally information on the bank business model, with higher securities to assets ratios being indicative of business model leaning heavier towards investment banking activities. We find that banks with larger OEA/TA are more efficient, which may be the result of being more diversified. In terms of price ratios, we note that larger banks have lower loan to price ratios, both actual and shadow, which may relate to their ability to generate income from non-traditional banking activities.

Liquidity is a critical issue for banks and their regulators. Table 5 shows that more liquids banks are more efficient and have higher loan price to deposits ratios.

Table 4. Efficiency and Relative Prices across other earnings assets to total assets ratio

OEA/TA		eff_{DT}	eff_{DI}	eff_{DO}	$\frac{S(L)}{P(L)}$	$\frac{S(D)}{P(D)}$	$\frac{S(LLR)}{P(L)}$	$\frac{P(L)}{P(D)}$	$\frac{S(L)}{S(D)}$	$\frac{P(L)}{P(OEA)}$	$\frac{S(L)}{S(OEA)}$
Small		0.8386	0.7824	0.8122	0.9941	1.0235	1.0527	1.0271	0.9711	1.0136	0.9922
		(0.1384)	(0.1771)	(0.1644)	(0.0306)	(0.1019)	(0.0532)	(0.0996)	(0.1244)	(0.0641)	(0.0319)
Medium		0.8089	0.7289	0.7698	0.9977	1.0226	1.0255	1.0363	1.0095	1.0213	1.0088
		(0.1585)	(0.2032)	(0.1787)	(0.0157)	(0.0205)	(0.0438)	(0.0148)	(0.0217)	(0.0158)	(0.0222)
Large		0.9147	0.8492	0.8805	0.9979	1.0249	1.0491	1.0495	1.0215	1.0386	1.0180
		(0.0923)	(0.1450)	(0.1096)	(0.0291)	(0.0288)	(0.0596)	(0.0249)	(0.0349)	(0.0269)	(0.0274)

Notes: OEA, TA, L, D, LLR are other earning assets, total assets, loans, customer deposits and loan loss reserves, respectively. P and S stands for price and shadow price, e.g. S(L) is the shadow price for loans.

Table 5. Efficiency and Relative Prices across liquid assets to total assets ratio

LA/TA	eff_{DT}	eff_{DI}	eff_{DO}	$\frac{S(L)}{P(L)}$	$\frac{S(D)}{P(D)}$	$\frac{S(LLR)}{P(L)}$	$\frac{P(L)}{P(D)}$	$\frac{S(L)}{S(D)}$	$\frac{P(L)}{P(OEA)}$	$\frac{S(L)}{S(OEA)}$
Small	0.8387	0.7754	0.8010	0.9930	1.0165	1.0383	1.0266	0.9740	1.0126	1.0012
	(0.1463)	(0.1942)	(0.1711)	(0.0185)	(0.0995)	(0.0482)	(0.0976)	(0.1181)	(0.0488)	(0.0308)
Medium	0.8250	0.7436	0.7882	1.0001	1.0311	1.0407	1.0381	1.0084	1.0257	1.0091
	(0.1583)	(0.1989)	(0.1787)	(0.0301)	(0.0335)	(0.0578)	(0.0238)	(0.0520)	(0.0367)	(0.0327)
Large	0.8987	0.8415	0.8734	0.9980	1.0236	1.0482	1.0478	1.0197	1.0355	1.0087
	(0.0963)	(0.1368)	(0.1086)	(0.0312)	(0.0247)	(0.0551)	(0.0248)	(0.0280)	(0.0368)	(0.0235)

Notes: LA, TA, L, D, OEA, LLR are liquid assets, total assets, loans, customer deposits, other earning assets and loan loss reserves, respectively. P and S stands for price and shadow price, e.g. S(L) is the shadow price for loans.

The cost to income (C/IC) ratio is often used as an indicator for the profitability of a bank in terms of its ability to generate revenue from its expenditures. There is no clear pattern emerging from Table 6 in terms of the relation between the cost to income ratio and bank efficiency. The relationship is positive under input orientation albeit negative under output orientation. The relationship is also negative between the C/IC ratio and the shadow prices of loans to deposits.

Table 6. Efficiency and Relative Prices across cost to income ratio

C/IC	eff_{DT}	eff_{DI}	eff_{DO}	$\frac{S(L)}{P(L)}$	$\frac{S(D)}{P(D)}$	$\frac{S(LLR)}{P(L)}$	$\frac{P(L)}{P(D)}$	$\frac{S(L)}{S(D)}$	$\frac{P(L)}{P(OEA)}$	$\frac{S(L)}{S(OEA)}$
Small	0.8645	0.7882	0.8282	0.9942	1.0195	1.0371	1.0432	1.0173	1.0258	1.0100
	(0.1237)	(0.1793)	(0.1453)	(0.0311)	(0.0352)	(0.0545)	(0.0277)	(0.0628)	(0.0339)	(0.0345)
Medium	0.8511	0.7699	0.8371	1.0018	1.0143	1.0416	1.0309	1.0055	1.0226	1.0085
	(0.1388)	(0.1980)	(0.1459)	(0.0227)	(0.0926)	(0.0525)	(0.0953)	(0.0778)	(0.0236)	(0.0277)
Large	0.8472	0.8027	0.7978	0.9949	1.0374	1.0489	1.0395	0.9796	1.0253	1.0006
	(0.1549)	(0.1704)	(0.1839)	(0.0269)	(0.0338)	(0.0543)	(0.0281)	(0.0881)	(0.0612)	(0.0244)

Notes: C, IC, L, D, OEA, LLR are total cost, income, loans, customer deposits, other earning assets and loan loss reserves, respectively. P and S stands for price and shadow price, e.g. S(L) is the shadow price for loans.

Greater reliance on deposits is an indicator of more stable source of funding for banks. Table 7 reveals a U-shaped relationship between the deposits to total funds ratio and bank efficiency.

Table 7. Efficiency and Relative Prices across deposits to total funding ratio

D/TF	eff_{DT}	eff_{DI}	eff_{DO}	$\frac{S(L)}{P(L)}$	$\frac{S(D)}{P(D)}$	$\frac{S(LLR)}{P(L)}$	$\frac{P(L)}{P(D)}$	$\frac{S(L)}{S(D)}$	$\frac{P(L)}{P(OEA)}$	$\frac{S(L)}{S(OEA)}$
Small	0.8618	0.8212	0.8238	0.9975	1.0342	1.0460	1.0252	0.9559	1.0148	1.0011
	(0.1449)	(0.1737)	(0.1712)	(0.0194)	(0.1065)	(0.0448)	(0.0999)	(0.1197)	(0.0605)	(0.0338)
Medium	0.8024	0.6919	0.7661	1.0031	1.0216	1.0282	1.0393	1.0190	1.0221	1.0141
	(0.1533)	(0.1980)	(0.1773)	(0.0226)	(0.0202)	(0.0547)	(0.0206)	(0.0225)	(0.0227)	(0.0287)
Large	0.8982	0.8473	0.8727	0.9910	1.0168	1.0520	1.0474	1.0271	1.0360	1.0039
	(0.0980)	(0.1331)	(0.1037)	(0.0351)	(0.0209)	(0.0583)	(0.0263)	(0.0258)	(0.0312)	(0.0234)

Notes: TF, D, L, OEA, LLR are total funds, customer deposits, loans, other earning assets and loan loss reserves, respectively. P and S stands for price and shadow price, e.g. S(L) is the shadow price for loans.

Tables 8 and 9 show that banks at the upper tertile of impaired loans to total loans and loan loss reserves to interest margin ratios are less efficient than those in the lower tertile.

Table 8. Efficiency and Relative Prices across Impaired loans to gross loans ratio

IML/GL		eff_{DT}	eff_{DI}	eff_{DO}	$\frac{S(L)}{P(L)}$	$\frac{S(D)}{P(D)}$	$\frac{S(LLR)}{P(L)}$	$\frac{P(L)}{P(D)}$	$\frac{S(L)}{S(D)}$	$\frac{P(L)}{P(OEA)}$	$\frac{S(L)}{S(OEA)}$
Small	Average	0.8848	0.8002	0.8844	1.0010	1.0159	1.0354	1.0301	1.0113	1.0144	1.0089
	Std. Dev	0.1095	0.1754	0.0994	0.0176	0.0242	0.0485	0.0108	0.0429	0.0222	0.0311
Medium	Average	0.8295	0.7414	0.8004	0.9993	1.0246	1.0448	1.0414	1.0055	1.0222	1.0082
	Std. Dev	0.1358	0.1823	0.1439	0.0191	0.0220	0.0467	0.0222	0.0688	0.0509	0.0268
Large	Average	0.8484	0.8191	0.7785	0.9905	1.0305	1.0472	1.0416	0.9855	1.0376	1.0019
	Std. Dev	0.1633	0.1833	0.2003	0.0390	0.1013	0.0647	0.1021	0.1075	0.0451	0.0299

Notes: IML, GL, L, D, OEA, LLR are impaired loans, gross loans, loans, customer deposits, other earning assets and loan loss reserves, respectively. P and S stands for price and shadow price, e.g. S(L) is the shadow price for loans.

Table 9. Efficiency and Relative Prices across loan loss reserves to interest margin ratio

LLR/IM	eff_{DT}	eff_{DI}	eff_{DO}	$\frac{S(L)}{P(L)}$	$\frac{S(D)}{P(D)}$	$\frac{S(LLR)}{P(L)}$	$\frac{P(L)}{P(D)}$	$\frac{S(L)}{S(D)}$	$\frac{P(L)}{P(OEA)}$	$\frac{S(L)}{S(OEA)}$
Small	0.9461	0.9216	0.9258	0.9912	1.0194	1.0607	1.0325	0.9840	1.0244	1.0000
	(0.0469)	(0.0691)	(0.0410)	(0.0339)	(0.0960)	(0.0596)	(0.0991)	(0.1164)	(0.0609)	(0.0256)
Medium	0.8682	0.7895	0.8497	0.9956	1.0190	1.0470	1.0447	1.0127	1.0315	1.0039
	(0.0903)	(0.1281)	(0.0930)	(0.0258)	(0.0227)	(0.0477)	(0.0242)	(0.0516)	(0.0348)	(0.0303)
Large	0.7492	0.6509	0.6885	1.0045	1.0334	1.0188	1.0356	1.0055	1.0174	1.0150
	(0.1686)	(0.2064)	(0.1924)	(0.0178)	(0.0373)	(0.0446)	(0.0164)	(0.0435)	(0.0184)	(0.0301)

Notes: LLR, IM, L, D, OEA, LLR are loan loss reserves, interest margin, loans, customer deposits, other earning assets and loan loss reserves, respectively. P and S stands for price and shadow price, e.g. S(L) is the shadow price for loans.

4. Conclusion

In this paper we have studied the performance of the CEE banking industry by explicitly modelling loan losses as an undesirable by-product of the loan production process. Recognising that bank input and output prices used in empirical studies are of questionable quality, we approached the problem of estimating the opportunity cost of bank inputs and outputs as a shadow price problem. We modelled technology using parametric forms of directional distance functions, and used the estimated parameters of the distance functions and knowledge of cost or revenue to obtain shadow prices for bank inputs and outputs, respectively. We also used crossover pricing rules to obtain shadow prices for inputs and outputs under profit maximisation.

We find that on average bank efficiency is highest in Estonia among the CEE countries. Recognising that Estonia also boasts the highest bank capitalisation in the CEE, we may infer that our findings are consistent with the franchise value hypothesis, i.e. better capitalised banks are also those with better management practices, which are put in place to protect the charter value of the financial institution. Our results also show that shadow prices for bank inputs and outputs differ significantly from observed price proxies typically used in the estimation of bank cost, revenue and profit functions. While this finding is not surprising, its implications deserve due attention among academics and practitioners. For example, differences between shadow and actual price ratios suggest that the output mix, input mix or both may not be consistent with revenue maximisation, cost minimisation, or profit maximisation, respectively.

Prices for problem loans are not observable, hence our approach provides an avenue for computing shadow prices for bad outputs in banking. This is important since it provides us with a quantitative assessment of the loss of good output (loans) needed to lower the bad output (problem loans) by a unit. This is particularly relevant in the current low interest environment where banks are under pressure to raise loans to improve profitability.

References

Aigner D.J., Chu, S.F. (1968), On estimating the industry production function, “The American Economic Review”, vol. 58, pp. 826-839.

Cuesta R.A., Zofío J.L. (2005), Hyperbolic efficiency and parametric distance functions: with application to Spanish savings banks, “Journal of Productivity Analysis”, vol. 24 no. 1, pp. 31-48.

Deloitte (2012), The banking sector in Central Europe performance overview, December.

Färe R., Grosskopf S., Margaritis D. (2017), Shadow pricing. Mimeo.

Färe R., Grosskopf S., Weber W.L. (2001), Shadow prices of Missouri public conservation land, “Public Finance Review”, vol. 29 no. 6, pp. 444-460.

Färe R., Sung K.J. (1986), On second-order Taylor's-series approximation and linear homogeneity, “Aequationes Mathematicae”, vol. 30 no.1, pp. 180-186.

Fries S., Taci, A. (2005), Cost efficiency of banks in transition: evidence from 289 banks in 15 post-communist countries, “Journal of Banking & Finance”, vol. 29 no. 1, pp. 55-81.

Koutsomanoli-Filippaki A., Margaritis D., Staikouras C. (2009a), Efficiency and productivity growth in the banking industry of Central and Eastern Europe, “Journal of Banking & Finance”, vol. 33 no. 3, pp. 557–567.

Koutsomanoli-Filippaki A., Margaritis D., Staikouras, C. (2009b), Profit efficiency in the banking industry of Central and Eastern Europe: A directional technology distance function approach, “Managerial Finance”, vol. 35 no. 3, pp. 276–296.

Sealey C.W., Lindley J.T. (1977), Inputs, outputs, and a theory of production and cost at depository financial institutions, “The Journal of Finance”, vol. 32 no. 4, pp. 1251-1266.

Spierdijk L., Shaffer S., Considine T. (2017), How do banks adjust to changing input prices? A dynamic analysis of US commercial banks before and after the crisis, "Journal of Banking & Finance", vol. 85 no. C, pp. 1-14.

Yildirim H.S., Philippatos G. (2007), Efficiency of banks: recent evidence from the transition economies of Europe, 1993-2000, "The European Journal of Finance", vol. 13 no. 2, pp. 123-43.

Nakłady i wyniki cenowe w bankowości: zastosowanie w krajach Europy Środkowo-Wschodniej

Streszczenie

Cel: Problemem związanym z badaniami nad wydajnością i produktywnością w bankowości jest to, że niektóre cenowe nakłady i wyniki wykorzystywane do szacowania funkcji kosztów, przychodów i zysków mogą cechować się wątpliwą jakością i tym samym wpływać na wiarygodność mierników kondycji finansowej. Autorzy zwracają uwagę na tę kwestię i koncentrują się na systemach bankowych w Europie Środkowo-Wschodniej, gdzie, dyskusyjnie, problem ten może być nawet bardziej palący.

Metodyka badań: Autorzy zastosowali formy parametryczne funkcji kierunkowych, aby uzyskać ceny cienie bankowych nakładów i wyników i porównali je z aproksymantami cen typowo stosowanymi w badaniach empirycznych. Główną ideą było wykorzystanie kosztu, przychodu i maksymalizacji zysku jako kryteriów optymalizacji w celu wyprowadzenia zasad cenowych, które pozwoliły na znalezienie cen cieni zarówno dla nakładów, jak i wyników. Wykazano, jak wiedza na temat ceny jednego czynnika może być wykorzystana do wyników cenowych, a także, jak wiedza na temat ceny jednego wyniku może być wykorzystana do nakładów cenowych wraz z informacją o ilościach nakładów i wyników. Zastosowano również koszt całkowity do nakładów cen cieni oraz przychód całkowity do wyników cen cieni.

Wnioski: Badania wykazały różnice pomiędzy cenami cieniami a aktualnymi cenami, sugerując, że mix nakładów i / lub wyników może nie być spójny z minimalizacją kosztów bądź maksymalizacją przychodów czy zysków. Stwierdzono także, że najwyższa wydajność banków występuje średnio w Estonii, chlubiącej się też najwyższą stopą kapitalizacji banków w Europie Środkowo-Wschodniej.

Wartość artykułu: Badanie wyraźnie odróżnia się od tradycyjnej literatury dotyczącej wydajności i produktywności poprzez koncentrację na cenach i polityce cenowej i ich oddziaływaniu na nakłady i wyniki.

Ograniczenia: Ceny nie są łatwo zauważalne w odniesieniu do problemów z pożyczkami. Z tego powodu przedstawione w artykule podejście wskazuje na drogę pozwalającą obliczyć ceny cienie w przypadku złych wyników w bankowości. Jest to istotne, ponieważ stanowi oznakę utraty dobrych wyników, aby obniżyć złe wyniki jednostki.

Słowa kluczowe: parametryczne funkcji kierunkowych, wydajność banków, ceny cienie, bankowość w Europie Środkowo-Wschodniej

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