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The cost-efficiency and productivity growth of euro area banks

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Abstract

We use an industrial organisation approach to quantify the size of Total Factor Productivity Growth (TFPG) for euro area banks after the crisis and decompose it into its main driving factors. In addition, we disentangle permanent and time-varying inefficiency in the banking sector. This is important because lack of distinction may lead to biased estimates of inefficiency and because the set of policies needed in both cases is different. We focus on 17 euro area countries over the period 2006 to 2017. We find that cost efficiency in the euro area banking sector amounted to around 84% on average over the 2006 to 2017 period. In addition, we observe that Total Factor Productivity growth for the median euro area bank decreased from around 2% in 2007 to around 1% in 2017, with technological progress being the largest contributor, followed by technical efficiency. Given the need to boost productivity and enhance profitability in the euro area banking sector, these findings suggests that bank's efforts in areas such as rationalisation of branches, digitalisation of business processes and possibly mergers and acquisitions should be intensified.

Key words: euro area, banking sector, financial stability, bank productivity, total factor productivity, cost-efficiency frontier, panel data, time-varying inefficiency, permanent inefficiency

JEL Classification: C23, D24, G21

Non-technical summary

The efficiency of banks is highly relevant for financial stability, in particular in a low-interest rate environment, which implies additional challenges for banks. In particular, weak profitability and overcapacity have often been mentioned as challenges for the euro area banking sector in recent years. Against this background, the cost-efficiency and productivity of euro area banks requires further improvements going forward.

The literature has traditionally used accounting indicators, such as the average cost (AC) of a bank or the cost to income ratio (CIR) to assess efficiency. These indicators are easy to compute but ill equipped to properly capture efficiency. The AC for a bank is highly dependent on the business model of the institution, its size and various country specific factors outside the control of the bank. The CIR, while capturing several important aspects of bank performance, also partly depends on country-specific factors, such as the cost of labour.

In light of these shortcomings, we contribute to the empirical literature by using an industrial organisation approach to compute Total Factor Productivity (TFP) growth in the euro area banking sector, *i.e.*, the growth in output not explained by growth in the amount of inputs used. More specifically, we estimate a trans-log cost function to compute each of the components of Total Factor Productivity growth, namely overall technical efficiency, technological progress and the equity and scale effects. In addition, to the knowledge of the authors, this is the first study that disentangles permanent and time-varying inefficiency in the euro area banking sector. The sample consists of a panel of commercial, cooperative and savings banks from 17 euro area countries over the period from 2006 to 2017.

Technical efficiency measures the banks' relative ability to convert inputs (financial capital, labour and fixed assets) into outputs (loans and investments), while minimizing costs. It is estimated based on frontier analysis where the most efficient bank is the one that incurs the lowest costs to generate a given amount of output at predetermined input prices. An advantage of this technique is that it controls for differences in banks' outputs and the input prices they incur, thus allowing comparisons between banks of different sizes, ownership structures, specialisation, etc.

We find that cost efficiency for the median euro area bank amounted to around 84% on average over the 2006 to 2017 period. In other words, if the median bank would operate on the technical efficiency frontier, it could produce the same level of output with 84% of the current costs. These results are in line with the majority of recent research in this field. Moreover, we find that the largest part of bank inefficiency is persistent, suggesting that structural long-term factors (such as location, client structure, macroeconomic environment, regulation, etc.) play a bigger role than time-specific factors. We also find that larger institutions have lower efficiency scores, which points to the fact that larger institutions are more complex to manage. Finally, our results suggest that more efficient banks tend to have lower ACs and lower CIRs, as expected. They are also more profitable, have lower credit risk and tend to be better capitalised.

TFP is also affected by changes in technological progress, the cost of equity and economies of scale. We find that the rate of technological progress for the median euro area bank amounted to 1.7% on average over the period 2006 to 2017. Estimations for the shadow cost of equity show an increase after the start of the global financial crisis (to about 6.9%), suggesting that the reward for being a better capitalised bank increased in times of financial stress. Thereafter, the shadow cost of equity exhibited a trend decline. We also find that economies of scale tend to be larger for smaller institutions, although the largest institutions also experience economies of scale. For the median euro area bank, they stood at around 9% on average over the period.

Taking all components together, we observe that Total Factor Productivity in the euro area banking sector decreased over the last decade (from above 2% in 2007 to below 1% in 2017). This is undesirable given the need to enhance profitability. Our findings suggest that banks should enhance their efforts in areas such as branch rationalisation, digitalisation of business processes and possibly mergers and acquisitions. However, it might take some time until such cost cutting activities bear fruits. In addition, they usually require substantial investments upfront.

1. Introduction

The analysis of efficiency in the euro area banking sector is very important for financial stability. Given that banks are the largest providers of credit to companies and households in the euro area, an efficient banking sector is important to ensure low lending rates and high lending volumes, hence stimulating the economy. Also, a more efficient banking sector should improve the transmission of monetary policies (Jonas and King, 2008). Moreover, banks that are more efficient are expected to be more profitable, better capitalised and more resilient to shocks. In recent years, however, the banking sector appears to be challenged by weak profitability and overcapacity, which calls for further measures to improve the health of the euro area banking sector.

The literature has traditionally used accounting indicators to proxy efficiency in the banking sector, such as the average cost (AC) of a bank, defined as the ratio between total costs and total assets, and the cost to income ratio (CIR). While these indicators are easy to compute, they are in fact ill equipped to capture efficiency in the banking sector. The AC is strongly dependent on the business model of the institutions and their size. It also depends on various country specific factors, which are outside the control of bank management. The CIR is simultaneously determined by several bank and country-specific aspects (such as bank productivity, efficiency, etc.). Moreover, income is affected by credit risk (at least indirectly), further distorting the estimation of efficiency by means of the CIR.

In light of these shortcomings, we contribute to the empirical literature by using an industrial organisation approach to compute Total Factor Productivity (TFP) growth in the euro area banking sector after the crisis and decompose it into its main driving factors. The estimation sample is based on a panel of commercial, cooperative and savings banks from 17 euro area countries over the period from 2006 to 2017. The analysis is based on the estimation of a trans-log cost function to capture banks' relative ability to convert inputs (financial capital, labour and fixed assets) into outputs (loans and investments), while minimising costs. The methodology is appealing because it allows the estimation of technical efficiency, technological progress and the equity and scale effects within the same econometric framework.

Our estimations also distinguish between persistent and time-varying efficiency. Disentangling these two components is important because it has been common practice to regard inefficiency as a period-by-period effect, independent from past levels and without a long-lasting impact. In particular, we implement the methodology developed by Kumbhakar *et al.* (2014) in order to separate bank-specific effects, persistent inefficiency, residual inefficiency and a random shock. To the knowledge of the authors, this is the first study that disentangles permanent and time-varying inefficiency in the euro area banking sector.[1]

The main findings of the paper are as follows. Overall cost efficiency for the median euro area bank amounted to around 84% on average over the period from 2006 to 2017. In other words, if the median bank would operate on the technical efficiency frontier, it could produce the same level of output with 84% of the current costs. Empirical evidence presented in this paper shows that the largest part of bank inefficiency in the euro area stems from persistent inefficiency, which suggests that structural long-term factors (such as location, client structure, macroeconomic environment, regulation, etc.) play a bigger role for bank inefficiency than time-specific factors. More efficient banks tend to record lower average costs, lower cost-to-income ratios, higher profitability, lower size (by market share), lower credit risk ratios and tend to be better capitalised. The rate of technological progress (*i.e.*, the effect of time on total costs) for the median euro area bank amounted to 2.5% on average over the period. Estimations for the shadow cost of equity, which are comparable to results from the Capital Asset Pricing Model (CAPM), show an increase after the start of the global financial crisis to about 6.9% in 2009, suggesting that the reward for being better capitalised increased in times of financial stress. Thereafter, the shadow cost of equity exhibited a trend decline, which coincided with the increase in capital ratios in euro area banks. Economies of scale tend to be larger for smaller institutions, although the largest institutions also exhibit economies of scale. For the median euro area bank, they stood at around 9% on average over the period. Taking all components together, we observe that Total Factor Productivity in the euro area banking sector decreased over the last decade (from above 2% in 2007 to below 1% in 2017), which is undesirable given the need to boost the profitability of euro area banks.

The rest of the paper is organised as follows. Section 2 presents the literature review. Section 3 presents the stochastic frontier analysis for the computation of TFPG. As mentioned before, the econometric model allows disentangling permanent and time-varying inefficiency in the euro area banking sector. The sample and descriptive data are presented in Section 4, including a short discussion about the usefulness of two of the most commonly used indicators for cost efficiency in the banking sector (the average cost and on the cost to income ratio). In Section 5 we present empirical results for the various components of TFPG, namely technical efficiency, technological progress and the equity and the scale effect. Section 6 concludes.

[1] Badunenko and Kumbhakar (2017) disentangle persistent and time-varying inefficiency in the Indian banking sector.

2. Review of the literature

There is a relatively large literature estimating cost functions in Europe and abroad based on frontier analysis. Boucinha *et al.* (2013) use a cost function to estimate Total Factor Productivity in the Portuguese banking system between 1992 and 2006, disentangling the impact of cost efficiency, return to scale and technological progress. The authors find that technological progress shifted the cost frontier downwards throughout their period, whereas efficiency remained unchanged. Scale economies have also contributed to boost productivity in the Portuguese banking sector. Tanna *et al.* (2017) look at the impact of financial liberalisation on banks' Total Factor Productivity in a sample of banks located in 88 countries over the period from 1999 to 2011. They argue that the net impact is positive, even taking into account the increased propensity to systemic banking crisis resulting from financial liberalisation.

Other studies focus on a narrower set of factors driving Total Factor Productivity. Spierdijk *et al.* (2017), looking at a large sample of US banks, argue that technological and economic (regulatory) changes further decreased the already low substitutability of key inputs for banks, making them more sensitive to input price changes.

Altunbas *et al*. (1999) use a stochastic cost frontier estimation technique to study the impact of technological progress (decomposed into pure, scale augmenting and non-neutral) on the costs of European banks over the period from 1989 to 1996. They find that the rate of reduction in costs due to technological progress increased between 1989 and 1996 and that large banks benefited more than small banks.

Altunbas *et al.* (2001) model cost efficiency, scale economies and technological change in the German banking market between 1989 and 1996, differentiating between ownership types (state-owned, mutual and private institutions). While all three bank ownerships benefit from widespread economies of scale, inefficiency measures indicate that public and mutual banks have slight cost advantages over their private sector competitors. Technological progress also appears to have made an important contribution to cost reduction in the German banking system over the period.

Niţoi and Spulbar (2015) use a heteroscedastic stochastic frontier model to investigate differences in cost efficiency of commercial banks in six Central and East European Countries over the period from 2005 to 2011. They find that banks in all the banking systems included in their study increased efficiency until 2008. However, they notice that efficiency either stagnated or declined after 2009.

Maudos *et al.* (2002) analyse cost and profit efficiency in a sample of European banks for the period 1993-1996 and find that profit efficiency is lower than cost efficiency. They also examine the drivers of the differences in efficiency between countries, focusing on size, specialisation, other characteristics specific to each bank and characteristics of the markets in which they operate. They conclude that there is a notably wide range of variation in efficiency levels in the banking systems of the European Union, the variation in terms of profit efficiency being greater than in terms of cost efficiency.

Other studies link inefficiency estimates to other banking variables. For example, Altunbas *et al.* (2007) and Fiordelisi *et al.* (2011) apply stochastic frontier analysis to estimate the efficiency of European banks and subsequently use time series econometric techniques to assess the inter-temporal relationship between bank efficiency, capital and risk over the period 1992-2000 and between 1995-2007, respectively. The two papers find opposite results regarding the relationship among these variables.

A caveat of most of the studies mentioned above is that they assume that all inefficiency is time varying, without controlling for unobserved, bank-specific effects or distinguishing between persistent and time-varying inefficiency. This is unfortunate because one of the biggest advantages of panel data models is their superior ability to take heterogeneity into account. From the studies mentioned above, only Maudos *et al.* (2002) account for bank-specific effects and time-varying inefficiency. However, their model fails to distinguish between time-varying and time-invariant inefficiency, confounding permanent inefficiency into heterogeneity. This is relevant because an important line of research focused on panel data econometric models where bank-specific effects are separated from permanent inefficiency, while accounting for time-varying inefficiency at the same time. A model that fails to distinguish between permanent inefficiency and bank-specific effects is likely to yield biased estimates of inefficiency. Precisely, one of our main contributions is to disentangle permanent and time-varying inefficiency in a sample of commercial, cooperative and savings banks for 17 euro area countries over the period from 2006 to 2017. We expect permanent inefficiency to play a very important role in the banking sector and particularly so for those banks with the largest sunk costs (i.e., the largest banks). At the same time, while we expect inefficiency to play an important role as a driver of TFP growth, we expect technological progress to be the largest contributor, as traditionally found in the literature (Boucinha *et al.,* 2013).

3. Estimating Total Factor Productivity (TFP) growth for euro area banks

This section presents the methodology to estimate bank efficiency and decomposes the Total Factor Productivity growth (TFPG) of euro area banks into its main components based on the following equation:

$$TFPG = TEC + TPROG + SCALE + EQUITY \qquad (1)$$

Where, *TFPG* is Total Factor Productivity growth, *TEC* is the rate of growth in technical efficiency, *TPROG* is technological progress and *SCALE* and *EQUITY* are the scale efficiency change and the equity effect on total costs, respectively. All of the components are measured in percent.

Technical efficiency (TEC) measures the relative ability of a bank to convert inputs (financial capital, labour and fixed assets) into outputs (loans and investments), while minimising costs.[2] The most efficient bank is the one that has the lowest cost while generating a given amount of output, for given input prices. Therefore, the efficiency results here are relative (to the best practise bank), rather than absolute.

Technological progress (TPROG) captures the decline (or increase) in total costs over time, for a given amount of output and input prices. According to Baltagi and Griffin (1988) and Kumbhakar and Heshmanti (1996), technological progress can be divided into three components. The first is called "pure technological progress" and captures only on the impact of time on total costs. The second is called "scale-augmenting technological progress" and captures the change in the sensitivity of total costs with respect to time as output changes. The third component is called "non-neutral technological progress" and reflects the changes in the sensitivity of total costs to time, as input prices change.

The third and fourth components of TFPG are the so-called "scale effect" (SCALE) and "equity effect". The former captures the importance of operating at the optimal scale (Kumbhakar *et al.,* 2015) and the latter captures the impact of the shadow cost of equity and changes in the equity ratio on Total Factor Productivity growth. In particular, it measures the impact of a change in equity on bank costs in a particular year.

The four components of *TFPG* can be computed based on stochastic frontier analysis (SFA), the most widely used parametric method for measuring firm specific cost-efficiency.[3] The assumption behind this methodology is that the distance from the frontier is not entirely under the influence of the bank due to both random error and the functional form of the cost function.[4] The methodology is appealing because it allows the estimation of technical efficiency, technological progress and the equity and scale effects from the same econometric model.

Traditional panel data econometric models often cannot separate individual heterogeneity from unobserved, time-invariant inefficiency, as the model will tend to confound all time-invariant inefficiency into heterogeneity, captured by a single bank-specific effect in the

[2] Farrell (1957) pioneered the work on firm inefficiency and defined it as a waste of resources, measured by the ratio between minimal (derived from a benchmark firm) and observed production costs. This work provided the ground for the future development of frontier methods.

[3] The cost-efficiency frontier can also be computed using non-parametric approaches, based on linear programming. This approach works well with small samples and does not require a priori assumptions on the functional form of the best practise frontier. However, non-parametric techniques do not allow for random error in the model, making the efficiency scores sensitive to changes in the definition of inputs and outputs. Parametric approaches to cost-efficiency frontier analysis developed into three directions: stochastic frontier analysis (SFA) introduced by Aigner *et al.* (1977) and Battese and Corra (1977), distribution free approach (DFA) and thick frontier approach (TFA). In this paper we focus on SFA because TFA does not allow for computing bank specific efficiency while DFA does not compute year by year efficiency scores.

[4] Therefore, SFA is sometimes referred to as composed error, since the part of the cost that cannot be explained by outputs and input prices is divided into an idiosincratic random error and inefficiency.

model (Greene, 2005).[5] However, inefficiency might be partly persistent and partly time-varying. In fact, persistent inefficiency is likely to be important in the banking industry because there are large sunk costs associated with starting a bank and it requires several years of deposit base formation to succeed in the business. Moreover, it tends to be very costly to restructure a bank (downsize the number of staff, merge the bank with another institution, etc.).

In this paper, we thus apply the generalized true random-effects (GTRE) model proposed by Kumbhakar *et al.* (2014). This model allows decomposing the persistent bank-specific effect into a random bank-specific effect (capturing unobserved heterogeneity à la Greene, 2005) and a persistent technical inefficiency effect.[6] In total, this model decomposes the error term of the stochastic cost function into four components, namely: *i*) short-term (time-varying) inefficiency; *ii*) persistent (time-invariant) inefficiency; *iii)* a bank-specific effect, capturing heterogeneity across banks; and *iv*) a pure random component (Greene, 2005).[7]

Therefore, the stochastic cost function can be written as follows:

$$lnTC_{it} = \alpha_0 + lnTC(y_{it}, w_{it}; \beta) + \psi_i + \upsilon_{it}^+ + \eta_i^+ + u_{it} \qquad (2)$$

Where α_0 is a constant, *i* refers to the cross-sectional unit and *t* refers to time, TC_{it} represents total costs, $TC(y_{it},w_{it},\beta)$ is a function of outputs and input prices, y_{it} are outputs produced by bank *i* at time *t*, w_{it} are input prices, β is a vector of parameters, ψ_i and $\eta_i^+ > 0$ are a bank-specific effect and persistent (time invariant) inefficiency, respectively. $\upsilon_{it}^+ > 0$ and u_{it} are residual inefficiency and the random error, respectively. Considering that we include a bank-specific effect in this equation (ψ_i) we do not use environmental variables as additional explanatory variables for efficiency.[8] Finally, *ln* denotes the natural logartithm.

The function $TC(y_{it},w_{it},\beta)$ represents the cost frontier while the sum of the constant (including the bank-specific effect), the function $TC(y_{it},w_{it},\beta)$ and the idiosincratic error represent the stochastic frontier. The difference between total costs and the stochastic frontier is the measure of cost ineficiency.

Equation (2) can be rewritten as:

$$lnTC_{it} = \alpha_{0*} + lnTC(y_{it}, w_{it}; \beta) + \alpha_i + \epsilon_{it} \qquad (3)$$

Where α_{0*}=$\alpha_0 + E(\eta_i^+) + E(\upsilon_{it})$, $\alpha_i = \psi_i + \eta_i^+ - E(\eta_i^+)$ and $\epsilon_{it} = \mu_{it} + \upsilon_{it}^+ - E(\upsilon_{it}^+)$.

To operationalise the calculation of the efficiency scores, we follow the three step approach recommended by Kumbhakar *et al.* (2014): *i*) We run the standard random-effects panel

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[5] Berger (1993 and 1995) show that bank specific effects tend to confound differences in bank size with inefficiency.

[6] The model was developed originally by Colombi *et al.* (2011).

[7] Kumbhakar (1991), Kumbhakar and Heshmati (1995) and Kumbhakar and Hjalmarsson (1995) proposed models with three components, namely a firm effect capturing only persistent inefficiency, a random component capturing time-varying technical inefficiency and a pure random error. The problem with these studies is that part of the persistent inefficiency might include unobserved firm effects.

[8] Including macro variables like GDP growth, HICP inflation, the Herfindahl-Hirschamn index, etc. in our equation does not influence the efficiency scores, as the methodology deals already with heterogeneity to a large degree. Including country dummies also leads to similar overall efficiency estimates. These results are available from the authors upon request.

regression model to estimate *β* and to predict the values of α_i and ϵ_{it}; *ii*) We estimate the time-varying technical efficiency, υ_{it}^{+} using the predicted values of ϵ_{it} from the first step. In particular, for $\epsilon_{it} = \mu_{it} + \upsilon_{it}^{+} - E(\upsilon_{it}^{+})$, we apply standard Stochastic Frontier Analysis (SFA) using Maximum Likelihood by assuming that μ_{it} is *i.i.d.* $N(0, \sigma_{\mu}^{2})$ and υ_{it}^{+} is $N^{+}(0, \sigma_{\upsilon}^{2})$; *iii*) We apply a similar approach as in the second step for $\alpha_i = \psi_i + \eta_i^{+} - E(\eta_i^{+})$. In particular, we apply standard SFA cross-sectionally assuming that ψ_i is *i.i.d.* $N(0, \sigma_{\psi}^{2})$ and η_i^{+} is $N^{+}(0, \sigma_{n}^{2})$ in order to obtain estimates of the persistent technical inefficiency component η_i^{+}; *iv*) Finally, overall technical efficiency is computed as the product of persistent technical efficiency and residual technical efficiency.

We use a trans-log cost function for *TC*(y_{it}, w_{it}, *β*) with three inputs and two outputs, while including both a linear and a quadratic time trend and the bank capital ratio to capture techological progress and risk considerations, respectively. In our framework banks produce loans and other earning assets (outputs), while utilising labour, physical capital and financial funds (inputs).[9] These variables are defined in Section 4. As a result, Equation (3) can be written as follows:

$$\begin{aligned} lnTC_{i,t} = \alpha_0 &+ \sum_{h=1}^{2} \alpha_h lny_{h,i,t} + \sum_{j=1}^{3} \beta_j lnw_{j,i,t} + \tau_1 lnE_{i,t} + t_1 T \\ &+ \frac{1}{2}\left[\sum_{h=1}^{2}\sum_{k=1}^{2} \delta_{hk} lny_{h,i,t} lny_{k,i,t} + \sum_{k=1}^{3}\sum_{j=1}^{3} \gamma_{kj} lnw_{k,i,t} lnw_{j,i,t} + \varphi_1 lnE_{i,t} lnE_{i,t} \right. \\ &\left. + t_{11} T^2 \right] + \sum_{h=1}^{2}\sum_{j=1}^{3} \rho_{hj} lny_{h,i,t} lnw_{j,i,t} \\ &+ \sum_{h=1}^{2} \omega_h lny_{h,i,t} lnE_{i,t} + \sum_{h=1}^{2} \varphi_h T lny_{h,i,t} + \sum_{j=1}^{3} \theta_j lnw_{j,i,t} lnE_{i,t} \\ &+ \sum_{j=1}^{3} \vartheta_j T lnw_{j,i,t} + \psi_i + v_{it} + n_i + u_{it} \end{aligned} \tag{4}$$

Where *i* denotes the cross-sectional unit and *t* denotes the time period, $y_h (h = 1{,}2)$ is output, $w_j (j = 1{,}2{,}3)$ are input prices, lnE_t is the natural logarithm of the capital ratio, and *T* is a time trend.

In order to guarantee linear homogeneity in factor prices, we assume the following:

$$\textstyle\sum_{j=1}^{3} \beta_j = 1\, ; \sum_{j=1}^{3} \gamma_{kj} = 0 \;\; \forall k ; \sum_{j=1}^{3} \rho_{hj} = 0 \; \forall h \tag{5}$$

To implement linear homogeneity into the trans-log cost function, it is necessary and sufficient to apply the following standard symmetry restrictions:

[9] Maudos *et al.* (2002), Lensink *et al.* (2008) and Lozano-Vivas and Pasiouras (2010) did not include a trend in the cost function. This would assume that the frontier is constant over time and consequently all the productivity changes would be attributed to changes in cost efficiency or changes in economies of scale.

$$\delta_{hk} = \delta_{kh}\ \forall h,k \text{ and } \gamma_{kj} = \gamma_{jk}\ \forall j,k \tag{6}$$

Therefore, to impose linear homogeneity restrictions, we normalize the dependent variable and all input prices by the price of labour (w_1).[10]

When estimating ineficiency for a large group of euro area banks, the question arises whether to estimate a common frontier for all banks or rather country-specific frontiers. The latter is usually justified when country specific circumstances affect the best practise banks. However, estimating country-specific frontiers is challenging for some euro area countries where there are not enough data for a meaningful estimation using the parametric approach. Also, integration and liberalisation of banking services in the context of the single monetary area, the single passport for financial services and recent progress with the European banking union speak in favour of estimating a single frontier, notwithstanding the fact that the operating environment for banks in the euro area remains somewhat heterogeneous.[11]

A related question is whether the frontier should be estimated for different types of banks (commercial banks, saving banks, cooperative banks, etc.). A global frontier allows comparison of efficiency of different ownerships relative to the best practice in the sector, whereas the latter only pemits comparison of efficiency among the same ownership. Hence, we follow Altunbas *et al.* (2007) and estimate a global cost-efficiency frontier for all ownerships and countries in the sample.

4. Data

Our dataset consists of a panel of commercial, cooperative and savings banks for the period 2006-2017 gathered from BankFocus.[12] Banks are classified as commercial if they are mainly active in retail, wholesale and private banking (*i.e.*, universal banks). Savings and cooperative banks are mainly active in retail banking (with the latter having a cooperative ownership structure).[13] After applying certain rules to remove institutions with unreliable or low quality data, or banks that might have been misclassified, our sample consists of an unbalanced panel of between 1.441 and 2.062 banks (depending on the year) from 17 euro area countries.[14]

[10] The econometric results are according to expectations and are available upon request.

[11] See Fiordelisi and Molyneux (2006) for a discussion on common versus country-specific frontier analysis.

[12] Data were collected via BankFocus (previously Bankscope) based on Moodys (previously Fitch).

[13] Other business models, such as real estate and mortgage banks were not included in the sample despite the importance of real estate financing for the euro area. Given that these banks are also involved in project development, their financial ratios are difficult to compare with the three categories considered in this analysis.

[14] We removed banks that: a) Recorded a change in the gross value of total assets of more than 50% in a particular year; b) Reported negative loans or securities; c) Reported deposits higher than total assets; d) Reported total costs (without value adjustments) above 30% of assets; e) Have a gross loans-to-total assets ratio below 33% or above 90%, to remove institutions that do not provide loans to the economy or that serve as SPVs; and f) Hold average assets for the whole period of below euro 50 million (small banks). Bank level information is not available for Latvia and Lithuania.

The distribution of banks by business model and country is presented in **Table 1**. The Table shows that more than half of the banks in our sample are located in Germany. The reason is that Germany has a large system of cooperative and savings banks. Other countries with a relatively large presence in the sample are Italy (large number of cooperative banks) and Austria (savings banks). Regarding business models, the Table shows that the majority of banks are cooperative and savings banks.

Table 1: Minimum and maximum number of banks per country and business model during the period 2006-2017

	Specialisation			
Countries	**Commercial banks**	**Cooperative banks**	**Savings banks**	**All banks**
Austria	13/20	32/56	43/74	88/150
Belgium	6/11	2/4	1/3	9/18
Cyprus	1/9	1/2	1/1	3/12
Estonia	1/1	0/0	0/0	1/1
Finland	2/13	1/3	1/8	4/24
France	41/51	39/61	5/11	85/123
Germany	23/44	555/656	343/425	921/1125
Greece	2/5	1/1	0/0	3/6
Ireland	1/5	0/0	0/0	1/5
Italy	30/38	237/314	13/22	280/374
Luxembourg	3/13	1/7	1/1	5/21
Malta	2/5	0/0	0/0	2/5
Netherlands	3/13	1/1	1/1	5/15
Portugal	2/7	1/4	1/74	4/85
Slovakia	3/7	0/0	1/2	4/9
Slovenia	5/9	2/2	1/1	8/12
Spain	7/19	8/47	3/11	18/77
Total EA	145/270	881/1158	415/634	1441/2062

Source: Author's calculations based on BankFocus.

Table 2 illustrates some key features of the three types of banks. As expected, commercial banks are, on average, the largest institutions (holding on average assets of 68.9 billion euro at end-2017). They also possess on average the largest share of loans to total assets (approximately 66.0%), while the share of other earning assets is broadly comparable across banks. Cooperative and savings banks are relatively more dependent on customer deposits, while commercial banks have a somewhat more diversified source of funding. Commercial banks also seem to recruit more expensive – and probably more skilled – staff, as they tend to offer a wider range of products to a broader range of customers, often also in foreign countries. Also commercial banks' AC are higher. Differences in equity to assets, the price of physical capital and the price of funds, are relatively small. However, differences among banks are significant, even within the same group of banks.

Table 2: Key features per bank type
(Data for end-2017)

			Total assets (bn. of euros)	Loans to assets	Other earning assets to assets	Customer deposits to assets	Price of labour (th. of euros)	Price of funds	Price of physical capital	Equity to assets	Average cost
Specialisation	Commercial	Min.	0.1	34.2%	0.0%	0.8%	44.1	0.1%	27.2%	5.7%	0.7%
		Mean	68.9	65.7%	25.8%	71.5%	75.2	0.6%	114.8%	9.6%	3.0%
		St.dev.	220.0	13.6%	12.6%	22.5%	17.8	0.4%	62.8%	3.5%	2.0%
		Max.	1960.0	89.6%	66.0%	99.0%	95.4	1.2%	223.4%	15.7%	17.2%
	Cooperative	Min.	0.1	33.0%	4.6%	14.8%	44.1	0.1%	27.2%	5.7%	0.8%
		Mean	5.6	61.7%	35.4%	78.5%	64.1	0.5%	81.5%	9.9%	2.3%
		St.dev.	63.3	12.2%	12.5%	15.2%	11.6	0.3%	47.0%	2.4%	0.9%
		Max.	1760.0	89.5%	66.9%	99.4%	95.4	1.2%	223.4%	15.7%	22.0%
	Savings	Min.	0.1	33.1%	5.6%	27.1%	44.1	0.1%	27.2%	5.7%	1.2%
		Mean	6.7	63.3%	32.9%	84.2%	58.6	0.5%	113.5%	9.9%	2.6%
		St.dev.	89.0	12.3%	12.7%	9.7%	9.7	0.3%	57.9%	2.3%	0.6%
		Max.	2130.0	89.5%	68.3%	98.9%	95.4	1.2%	223.4%	15.7%	6.8%
	All euro area	Min.	0.1	33.0%	0.0%	0.8%	44.1	0.1%	27.2%	5.7%	0.7%
		Mean	14.4	62.8%	33.3%	79.5%	63.9	0.5%	95.1%	9.9%	2.5%
		St.dev.	108.0	12.5%	13.0%	15.4%	13.1	0.3%	54.7%	2.5%	1.0%
		Max.	2130.0	89.6%	68.3%	99.4%	95.4	1.2%	223.4%	15.7%	22.0%

Notes: The price of labour is calculated as personnel expenses over the total number of employees; the price of physical capital is calculated as the ratio of other overhead costs to non-earning assets; and the price of funds is computed as the ration between interest costs and total liabilities.
Source: Author's calculations based on BankFocus.

There is a long-standing discussion in the literature regarding the distinction between bank outputs and inputs. We adopt the *accounting balance-sheet approach* of Sealey and Lindley (1977) and treat liabilities as inputs and assets as outputs. In particular, we view banks as firms that use labour, fixed assets and financial capital to produce loans and other earning assets.[15] This approach is different from the *value added approach*, which considers deposits as another output.[16]

Regarding the price of inputs, we compute the price of labour as labour expenses over the number of employees.[17] For the price of fixed assets, we use the ratio of other (non-labour)

[15] Boucinha *et al.* (2013) test for the inclusion of deposits as outputs following the methodology developed by Hughes and Mester (2003). Implementation of such test requires a breakdown of interest costs into those paid on deposits versus on other liabilities. Such granular data are not available for the sample under consideration.
[16] The *value-added approach* considers bank deposits as products because they contribute to create value added in the banking sector (generating fees and commissions, relationships with clients, etc.) and in the society in general (providing means of payments). Also, banks devote sizable resources to gather and manage deposits. See Berger *et al.* (1987) and Camanhol and Dyson (2005) for a discussion.
[17] Part of the literature computes the price of labour as the ratio between personell expenses and total assets. By calculating the price of labour relative to total assets one would actually capture labour productivity as well (Maudos *et al.*, 2002).

administrative costs to fixed assets. The price of funds is computed as the ratio between interest expenses and total liabilities. Total costs, our dependent variable, is computed as the sum of these three components. By including interest costs (cost of financing,) we capture a more comprehensive overview of banks' business profiles.[18] This specification of outputs and inputs is similar to most of the previous studies. In particular, most of the literature has estimated cost functions with the same inputs while the number of outputs has varied from two to five.[19]

Finally, we follow Berger and Mester (1997), Hughes and Mester (2008) and Fiordelisi *et al.* (2011) and use equity to total assets as a quasi-fixed input to control for differences in risk preferences. **Table 3** presents descriptive statistics about the variables included in the model.

Table 3. Variables included in the cost function

	Unit	Obs.	Mean	Std. Dev.	Min	Max
Dependent variable						
Total costs	Mill. EUR	21,224	352	2827	-1	101000
Outputs						
Gross loans	Mill. EUR	21,224	6,384	47,200	9.117363	1,220,000
Other earning assets	Mill. EUR	21,224	4,325	41,200	0.009	1,180,000
Prices						
Personnel costs per employee	000 EUR	19,332	58.4	12.0	38.7	95.4
Interest expenses to total liabilities	%	21,224	2%	1%	0%	4%
Other overheads to non-earning assets	%	19,829	85%	44%	27%	225%
Semi-fixed input						
Total equity to total assets	%	21,224	9%	3%	4%	16%

Source: Author's calculations based on BankFocus data.

5. Empirical results

This section computes Total Factor Productivity (TFP) growth in the euro area banking sector, *i.e.*, the growth in output not explained by growth in the amount of inputs used. It is based on Equation (1) presented in Section 3. As mentioned before, the estimated trans-log cost function (Equation 4 above) can be used to compute each of the components of Total Factor Productivity growth, namely overall technical efficiency, technological progress and the equity and the scale effect.

The first sub-section (Sub-section 5.1) looks at technical efficiency in the euro area banking sector. It starts by presenting two of the most commonly used indicators for cost efficiency in the banking sector (the average cost -AC- and the cost to income ratio –CIR-) and their

[18] Altunbas *et al.* (2007) also compute total costs including operating and financial costs.

[19] A few studies that have estimated a cost function with the same inputs are Altunbas *et al.* (1999), Altunbas *et al.* (2001), Maudos *et al.* (2002), Altunbas *et al.* (2007), Feng and Serleis (2009), Fiordelisi *et al.* (2011), Boucinha *et al.* (2012) and Tsionas and Kumbhakar (2014). Altunbas *et al.* (2001) focus on five outputs, namely mortgage loans, public loans, other loans, aggregate securities and off balance sheet items.

caveats. It then moves to present results from the frontier-based technical efficiency analysis. Sub-section 5.2 presents the results of the estimation of technological progress. The Sub-section presents the temporal evolution of the three components of technological progress, namely pure, scale-augmenting and non-neutral technological progress. Sub-section 5.3 presents the third component of Total Factor Productivity growth (TFPG) and is based on the estimation of the shadow cost of equity. The scale effect is presented in Sub-section 5.4 and requires the previous calculation of economies of scale. Finally, the four components are taken together to compute Total Factor Productivity growth (Subsection 5.5).

5.1. Technical efficiency

The average cost (AC) of a bank and the cost to income ratio (CIR) are two of the most commonly used indicators for measuring cost efficiency in the banking sector. AC is defined as the ratio between total costs (including administrative and interest expenses) and total assets of a bank. Regarding the CIR, different versions are available but the standard CIR is computed as the ratio between administrative costs and operating income. Two factors affect the numerator of the CIR (namely labour costs -quantity of employees and price of labour- and other administrative costs) while the denominator consists of the three most relevant income categories, namely net interest revenue, net fee and commission income and income from other items. These indicators are very easy to compute. However, both indicators are ill equipped to capture efficiency in the banking sector.

AC is strongly dependent on the size and business model of the bank. In particular, institutions oriented towards corporate clients will tend to invest fewer resources in physical infrastructure (branches) than retail oriented institutions. AC also depends on various country specific factors (*e.g.*, the cost of labour might be higher in more developed countries), which are largely outside the reach of bank management. Hence, AC is an indicator of average input prices for producing a unit of bank assets, rather than an indicator of bank efficiency.

Also, the CIR has two main drawbacks. First, it lumps together several aspects of bank performance, such as productivity, efficiency and various bank-specific, as well as country-specific factors. Regarding the latter, while banks can influence interest margins, if they have some degree of market power, global and country specific factors are arguably even more important determinants.[20] Labour costs also tend to be country specific, with bank managers having limited power to influence them. Second, the CIR is affected by credit risk (at least indirectly), further distorting the estimation of efficiency. In particular, non-performing loans (NPLs) lead to lower interest income and higher administrative and funding costs.

As a result, several factors affect the average cost and the CIR, distorting the estimation of bank efficiency derived from these indicators. By contrast, an advantage of stochastic

[20] Empirical evidence shows that euro area banks adjust sluggishly their interest rates on loans and deposits in response to changes in market interest rates (Gropp *et al.*, 2007), makings their margins more volatile and sensitive to environmental changes.

frontier analysis is that the resulting measure of cost efficiency controls for the fact that banks produce different outputs and pay different prices for inputs, therefore, allowing the comparison between banks of different sizes, ownership structures, specialisation, etc.

Based on the estimation of Equation (4), **Table 4** reports the overall technical efficiency of the euro area banking sector, together with the estimation of persistent and residual efficiency across bank's business models. The persistent component of efficiency amounted to about 88.2% while the residual efficiency component amounted to about 95.4% (on average for all banks) during the period from 2006 to 2017.[21] These findings suggest that the median bank uses 11.8% and 4.6% more resources than the bank that is at the efficiency frontier (for the euro area) due to permanent and time-varying factors, respectively. Hence, after controlling for bank heterogeneity and persistent efficiency, the share attributed to residual efficiency is relatively small. Put otherwise, structural long-term factors (such as location, client structure, macroeconomic environment, regulation, etc.) seem to play a bigger role for bank efficiency than factors that change over time.

Looking across business models, there seems to be little difference within residual efficiency, while the differences are larger for persistent efficiency. In particular, it is found that efficiency is higher for cooperative and savings banks compared with commercial banks. This finding suggests that structural differences across banks' business models play a more important role for efficiency than year-on-year changes in management decisions.[22] Overall bank efficiency, computed as the product between persistent (time invariant) and residual (time variant) efficiency, for the entire euro area banking sector, was around 84% over the period from 2006 to 2017. These findings are in line with those for US commercial banks (Feng and Serletis, 2009), Portuguese banks (Boucinha *et al.,* 2013), German banks (Altunbas *et al.*, 2001) and a sample of European banks (Maudos *et al.*, 2002).[23] In other words, our findings suggest that if the median bank would operate on the efficiency frontier, it could produce the same level of output with only around 84% of current costs.

[21] Changes in persistent efficiency over time reflect a change in the underlying market shares of the banks in the sample and changes in the sample *per se*.

[22] This evidence is supported by Altunbas *et al.* (2001) who find that mutual and saving banks in Germany have cost efficiency advantages over their private commercial banking counterparts. However, these authors do not distinguish between permanent and residual efficiency. At the same time, our methodology utilises two bank outputs (namely loans and other earning assets). However, it is possible that commercial banks are involved in other activities (such as derivatives trading, asset management, etc.) that are not counted as outputs in our framework but generate additional costs.

[23] By contrast, Fiordelisi *et al.* (2011) find much lower efficiency scores for European commercial banks over the period 1995-2007 (between 37% and 59%).

Table 4. Efficiency per bank specialisation
(median for all banks and each category)

	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Persistent efficiency												
Commercial	84.1%	83.8%	83.6%	83.5%	83.8%	83.5%	84.1%	84.3%	84.0%	83.9%	84.3%	84.0%
Cooperative	89.5%	89.5%	89.5%	89.6%	89.5%	89.5%	89.5%	89.5%	89.5%	89.1%	89.5%	89.4%
Savings	85.6%	85.8%	85.8%	85.8%	86.0%	86.1%	86.2%	86.1%	86.1%	86.0%	86.1%	86.0%
All banks	88.3%	88.3%	88.3%	88.3%	88.3%	88.3%	88.3%	88.3%	88.3%	87.9%	88.2%	88.1%
Residual efficiency												
Commercial	96.2%	96.1%	95.7%	95.5%	95.9%	95.7%	95.2%	95.4%	95.4%	95.4%	94.8%	94.5%
Cooperative	95.2%	95.4%	95.3%	95.2%	95.2%	95.2%	95.5%	95.4%	95.5%	95.3%	95.7%	96.4%
Savings	95.8%	95.3%	95.3%	95.0%	95.4%	95.7%	95.8%	95.7%	95.6%	95.6%	94.1%	95.4%
All banks	95.4%	95.4%	95.3%	95.1%	95.3%	95.4%	95.6%	95.5%	95.5%	95.4%	95.2%	95.9%
Overall efficiency												
Commercial	79.8%	80.1%	79.5%	79.5%	80.3%	79.7%	79.9%	79.7%	80.2%	79.8%	79.8%	79.4%
Cooperative	84.8%	85.1%	85.1%	84.9%	84.9%	85.1%	85.2%	85.2%	85.2%	84.5%	85.1%	85.6%
Savings	81.7%	81.5%	81.6%	81.1%	81.9%	82.4%	82.8%	82.4%	82.2%	81.8%	80.3%	81.2%
All banks	83.7%	83.9%	83.9%	83.8%	83.9%	84.1%	84.2%	84.0%	84.1%	83.5%	83.4%	83.8%

Note: The relative distance to the frontier for persistent and time-varying inefficiency is computed based on υ_{it}^{+} and η_i^{+}, respectively (as described in Equation 4).
Source: Author's calculations based on BankFocus data.

Looking at the evolution of efficiency across bank size, as measured by the respective market share in the country of origin, larger institutions tend to display lower overall efficiency scores (**Table 5**). In 2017, the overall efficiency score for banks above the 75th percentile was around 5.5 percentage points lower than for those below the 25th percentile.[24] This difference, which after a period of convergence, widened again more recently, seems to be mainly the result of differences in persistent efficiency. One reason that could explain why larger institutions are less efficient is that they are more difficult to manage, as they deploy a more sophisticated business model. On the other hand, larger institutions might invest more in other aspects of the business, such as brand value or strategy, which are focused mainly on increasing market power rather than on cost efficiency. As these activities are recorded in total costs but not in the bank outputs (they are intangible assets), they might lead to lower efficiency in these institutions. By contrast, residual efficiency seems to be broadly unrelated to size, suggesting that lower efficiency of larger institutions is a structural rather than a time-varying phenomenon.

Finally, we look at banks with different efficiency scores across several indicators (average cost, cost to income, etc.) (**Table 6**). Banks are divided into three groups: *i*) Banks with overall efficiency score below the 10th percentile (most inefficient banks); *ii*) The total sample; and *iii*) Banks with overall efficiency scores above the 90th percentile (most efficient banks). As expected, more efficient banks, according to the stochastic frontier analysis, also tend to record a lower cost-to-income ratio, higher profitability (measured by return on assets, ROA) and a larger share of high yield items in the balance sheet. Moreover, the most efficient banks tend to have lower credit risk ratios than the less efficient counterparts,

[24] Feng and Serletis (2009) also find that the largest commercial banks are less efficient than their smaller counterparts in a sample of US banks.

which suggests that they are more efficient at handling credit risk. These results are broadly in line with those of Boucinha *et al.* (2012) for Portugal and Niţoi and Spulbar (2015) for Central and Eastern Europe. Lastly, more efficient banks tend to be better capitalised.[25] On the one hand, this result suggests that higher profitability associated with higher efficiency allows banks to accumulate retained earnings and increase capital ratios. At the same time, this finding might also suggest that banks with a higher share of equity have the incentive to increase efficiency, since equity is the most expensive source of financing.[26]

Table 5.Efficiency by bank market share in the local market
(median for each category)

	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Persistent efficiency												
<25th pctile.	91.99%	91.56%	91.03%	91.03%	90.29%	90.30%	90.12%	90.51%	90.56%	90.23%	90.56%	90.61%
25th to 50th pctile.	89.29%	88.98%	88.57%	88.53%	87.46%	87.45%	87.45%	88.12%	88.26%	88.10%	88.15%	88.31%
50th to 75th pctile.	87.18%	86.55%	86.04%	85.97%	85.97%	85.97%	85.97%	86.04%	86.28%	86.23%	86.28%	86.59%
>75thpctile.	85.21%	85.64%	86.02%	86.23%	86.70%	86.81%	87.05%	86.48%	86.40%	86.12%	86.62%	85.96%
Residual efficiency												
<25th pctile.	95.82%	95.68%	95.79%	95.59%	95.25%	95.28%	95.32%	95.13%	95.06%	94.79%	95.61%	96.33%
25th to 50th pctile.	95.19%	95.27%	95.30%	95.22%	95.16%	95.32%	95.68%	95.52%	95.53%	95.35%	95.49%	96.16%
50th to 75th pctile.	95.18%	95.23%	95.16%	94.98%	95.37%	95.55%	95.84%	95.76%	95.73%	95.43%	94.77%	95.77%
>75thpctile.	95.55%	95.45%	95.15%	94.65%	95.45%	95.63%	95.64%	95.67%	95.78%	95.84%	94.75%	95.53%
Overall efficiency												
<25th pctille.	87.80%	87.32%	86.97%	86.72%	85.73%	85.89%	85.83%	85.83%	85.81%	85.29%	86.09%	86.64%
25th to 50th pctile.	84.88%	84.38%	84.28%	84.20%	83.09%	83.16%	83.60%	84.03%	84.08%	83.74%	83.65%	84.13%
50th to 75th pctile.	82.38%	82.07%	81.76%	81.46%	81.82%	82.25%	82.20%	82.43%	82.80%	82.56%	81.63%	82.70%
>75thpctile.	80.90%	80.94%	81.55%	81.27%	82.46%	82.58%	83.02%	82.26%	82.54%	82.14%	81.22%	81.17%

Note: The Table reports median efficiency scores (relative distance to the frontier) by bank size. The bank size is measured by the market share in the country of origin.
Source: Author's calculations based on BankFocus data.

[25] In this regard, it is important to note that since we included equity levels as a quasi-fixed input in the equation, our efficiency measures are not affected by the fact that some banks have higher equity levels and therefore a lower cost of liabilities.

[26] Fiordelisi *et al.* (2011) find that the link between bank efficiency and solvency runs both ways: more efficient banks become better capitalized and higher capital levels tend to have a positive effect on efficiency levels in European commercial banks. Altunbas *et al.* (2007) and Niţoi and Spulbar (2015) find that banks with lower solvency rates are more inefficient in Central and Eastern Europe and in European co-operative banks, respectively.

Table 6. Bank's characteristics by overall efficiency scores
(% if not stated otherwise; median)

	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Banks with efficiency below 10th pctile.												
Average cost	4.93%	4.72%	4.94%	5.23%	4.42%	3.99%	4.05%	3.72%	3.50%	3.35%	3.40%	3.02%
Cost to income	72.85%	75.82%	74.49%	71.89%	72.62%	72.72%	73.66%	72.98%	73.15%	74.89%	85.34%	81.48%
Loans to assets	55.48%	55.04%	55.26%	55.86%	52.26%	57.44%	58.65%	58.40%	57.88%	57.20%	57.67%	58.82%
Return on assets (ROA)	0.26%	0.22%	0.19%	0.21%	0.22%	0.19%	0.19%	0.19%	0.21%	0.17%	0.14%	0.17%
Market share	0.04%	0.05%	0.03%	0.04%	0.02%	0.02%	0.02%	0.03%	0.02%	0.03%	0.03%	0.04%
Credit risk	0.88%	0.74%	0.60%	0.78%	0.59%	0.34%	0.39%	0.42%	0.29%	0.30%	0.08%	0.14%
Equity to assets	6.45%	6.12%	5.66%	5.93%	6.07%	6.69%	7.03%	7.60%	7.65%	8.01%	8.76%	8.85%
All banks												
Average cost	4.33%	4.28%	4.52%	4.78%	4.02%	3.54%	3.50%	3.21%	2.99%	2.77%	2.59%	2.38%
Cost to income	65.69%	69.29%	70.27%	68.33%	66.67%	66.39%	66.90%	66.80%	66.85%	68.29%	72.62%	71.84%
Loans to assets	63.35%	62.72%	62.08%	62.08%	62.78%	63.58%	63.26%	63.16%	62.56%	63.30%	63.19%	63.61%
Return on assets (ROA)	0.41%	0.31%	0.24%	0.28%	0.28%	0.26%	0.26%	0.24%	0.25%	0.23%	0.22%	0.23%
Market share	0.03%	0.02%	0.02%	0.02%	0.01%	0.01%	0.01%	0.02%	0.02%	0.02%	0.02%	0.03%
Credit risk	0.73%	0.57%	0.63%	0.65%	0.57%	0.35%	0.31%	0.29%	0.22%	0.24%	0.12%	0.11%
Equity to assets	6.86%	6.95%	6.78%	7.01%	7.29%	7.79%	8.13%	8.56%	8.89%	9.02%	9.30%	9.55%
Banks with efficiency above 90th pctile.												
Average cost	3.84%	3.88%	4.28%	4.59%	3.59%	3.08%	3.09%	2.86%	2.61%	2.48%	2.30%	2.10%
Cost to income	63.16%	64.54%	66.89%	66.57%	66.37%	64.42%	65.17%	63.64%	63.61%	65.52%	70.05%	69.69%
Loans to assets	64.91%	64.68%	63.63%	63.51%	66.40%	65.69%	64.21%	64.30%	63.73%	65.04%	65.72%	64.39%
Return on assets (ROA)	0.53%	0.54%	0.30%	0.32%	0.37%	0.33%	0.34%	0.33%	0.35%	0.35%	0.32%	0.34%
Market share	0.03%	0.02%	0.02%	0.01%	0.02%	0.02%	0.02%	0.02%	0.03%	0.03%	0.03%	0.03%
Credit risk	0.49%	0.46%	0.56%	0.65%	0.53%	0.52%	0.49%	0.34%	0.31%	0.27%	0.11%	0.07%
Equity to assets	7.50%	7.99%	7.57%	7.82%	7.90%	8.50%	8.84%	8.99%	9.20%	9.21%	9.57%	9.97%

Notes: The average cost is the ratio between total costs and total assets. Cost to income is the ratio between operating costs and operating income. Credit risk is the ratio between loan loss provisions and total assets. The Z-score is calculated as: $\mathrm{Z} = (\mathrm{EAR} + \mathrm{ROA}^{3ya})/\sigma_{\mathrm{ROA}}^{3\mathrm{ya}}$, where EAR is the equity-to-asset ratio for the current period, $\mathrm{ROA}^{3\mathrm{ya}}$ is the 3-year moving average of ROA and $\sigma_{\mathrm{ROA}}^{3\mathrm{ya}}$ is the 3-year standard deviation of ROA.
Source: Author's calculations based on BankFocus data.

5.2. Technological progress[27]

Including a time trend in the cost function (linear, squared and interacted with other exogenous variables) allows for the estimation of technological progress, defined as the effect of time on total costs and computed as the partial derivative of total costs with respect to time ($TPROG = \partial lnTC_h/\partial t$). According to Baltagi and Griffin (1988) and Kumbhakar and Heshmanti (1996), technological progress can be divided into three

[27] Results reported in the following sections are based on the estimation of a trans-log cost function estimated with SFA methods. Hence, unlike before where we computed two elements of inefficiency (persistent and residual), other elements of total factor productivity growth are calculated directly from the same cost function.

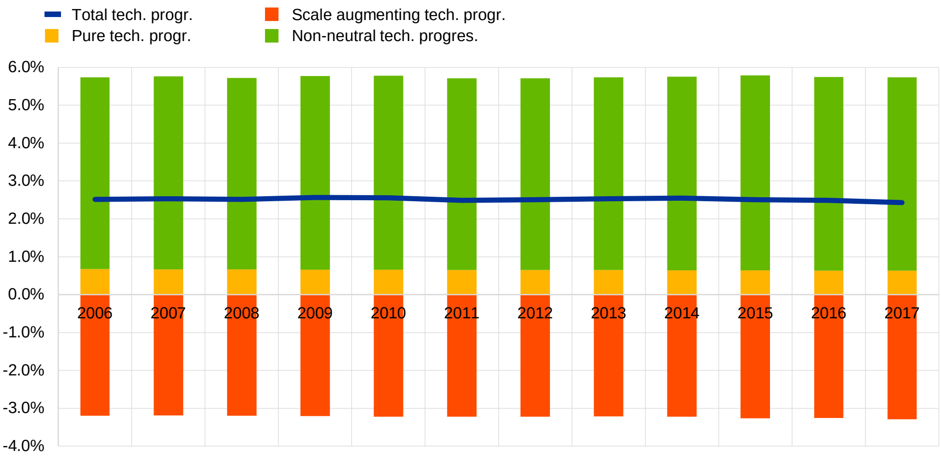
components. The first is called “pure technological progress” and depends only on the time trend. The second is called “scale-augmenting technological progress” and depends on the interaction terms between time and outputs, capturing the change in the sensitivity of total costs with respect to time as output changes. The third component is called “non-neutral technological progress” and reflects the changes in the sensitivity of total costs to time, as input prices change.

The evolution over time of the three components is presented in **Figure 1.** On average between 2006 and 2017, the annual rate of technological progress for the median euro area bank amounted to 2.4%. Altunbas *et al.* (2007) estimated a much higher rate of technological progress for German banks over the period 1989 to 1996 (10% on average). This finding might be affected by the fact that this period overlaps by and large with the introduction of internet and new computer technologies.[28] Altunbas *et al.* (1999) found a lower rate of technological progress for banks in fifteen European countries (between 2.8% and 3.6% over the period 1989 to 1996). Our results are also broadly in line with those reported by Boucinha *et al.* (2013), who estimated the technological progress of Portuguese banks between 2000 and 2006 to be around 2% to 3%. The rate of technological progress declined slightly in our sample, from 2.5% to 2.3%, potentially due to the wider adoption of internet and other technological advances which boosted technological progress in the earlier years, as mentioned before.

The largest component of technological progress is non-neutral, amounting to around 5.1% in the whole sample for the median euro area bank. This result is due to decreasing costs of funds in the euro area banking sector and implies that technological progress is mostly driven by factors that are outside the control of the banks. Pure technological progress is slightly positive, suggesting that costs themselves have a tendency to slightly decrease over time, holding constant the efficient scale of production for our two outputs and the shares of each input in total cost. Finally, the scale-augmenting component, or the sensitivity of total costs with respect to variations in the efficient scale of production remained stable at around -3.3%.

[28] It may also reflect a miss-specified model, as their econometric specification omits risk and cost of equity considerations.

Figure 1. The rate of technological progress and its components for the euro area banking sector *(median)*



Note: Technological progress leads to a decline in total costs.
Source: Author's calculations based on BankFocus data.

5.3. Scale effect

The fourth component of Total Factor Productivity growth (TFPG) is the so-called "scale effect". It is computed as the product between economies of scale and (weighted) output growth. This component captures the importance of operating at the optimal scale (Kumbhakar *et al.,* 2015). Indeed, economies of scale are not enough *per se* to guarantee an increase in bank productivity. For a bank to benefit from economies of scale, it needs to deliver a higher amount of outputs. Economies of scale are typically computed as the inverse of the output cost elasticity based on the trans-log cost function. The output cost elasticity shows the sensitivity of total costs to changes in output (*i.e.*, the sum of the partial derivatives of total costs with respect to each of the outputs; $E_{cy} = \sum_{h=1}^{2} \partial lnTC/\partial lny_h$). If the output cost elasticity equals one, a unit increase in output will result in the same increase in total costs and therefore the average cost will remain unchanged. If the output cost elasticity is below (above) one, the average cost decreases (increases) with an increase in output. For the trans-log cost function that we use in this analysis, the output cost elasticity is observation-specific (*i.e.*, it varies by bank and over time).

When calculating economies of scale in this traditional manner, the implicit assumption is a constant cost of equity. By contrast, Dijkstra (2013) and Hughes and Mester (2013) suggest that the price of equity falls as the amount of equity increases (Modigliani and Miller, 1958). Hence, better capitalised institutions will be perceived as less risky and therefore the bank will face lower liability costs. Also, higher capital levels can act as a signalling device, resulting in banks paying lower prices for other inputs as well. In particular, Hughes and Mester (2013) suggest a modified measure of economies of scale that accounts for the impact of the cost of equity on economies of scale:

$$SEC_{EQ} = SEC/(1 - SCOE) \qquad (7)$$

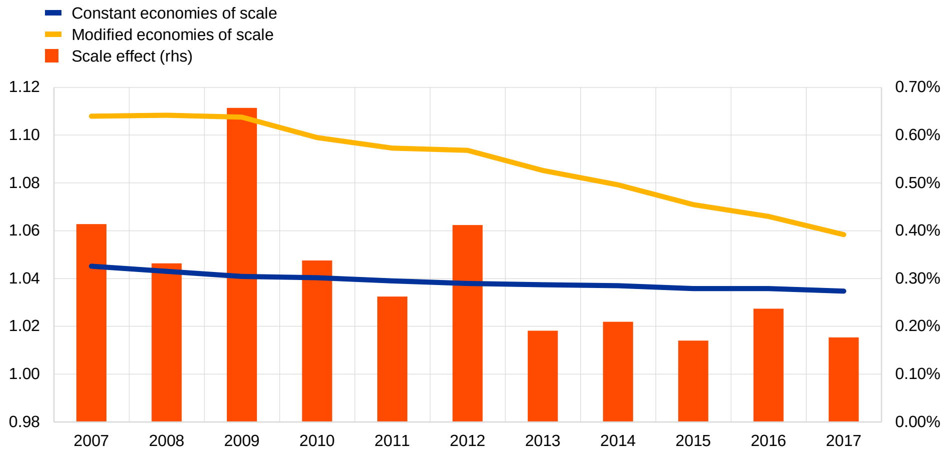
Where SEC_{EQ} is the modified measure of economies of scale, *SEC* is the traditional measure of economies of scale and *SCOE* is the shadow cost of equity, as defined in the next Sub-section.

The modified measure of economies of scale by bank size (grouped into four categories) and type of bank is reported in **Table 7**. Results show that they tend to be larger for the smaller institutions, although the largest institutions (those in category number four) also experience economies of scale.[29] The smallest and the largest institutions exhibited average economies of scale of about 1.10 and 1.07 over the sample, respectively. Regarding bank specialisation, economies of scale seem to be slightly larger for cooperative banks. These findings are consistent with those in Altunbas *et al.* (2001) for German banks, who report higher economies of scale for mutual and saving banks than for larger, commercial banks.

The modified measure of economies of scale, the constant measure of economies of scale and the scale effect are reported in **Figure 2**. Our results suggest that euro area banks exhibited economies of scale of around 9%, on average over the period. By comparison, the standard measure is lower, signalling economies of scale of around 4% on average. The modified measure of economies of scale was stable until 2009, when it started to decline (with one interruption in 2012). The modified measure of economies of scale reached approximately 6% at the end of the sample. These findings suggest that increasing outputs by a factor of one in 2017 led to an increase in total costs by a factor of 0.94.[30]

Finally, the scale effect (product between modified economies of scale and –weighted-output growth) peaked in 2009 and 2012 when bank products (loans and investments) rebounded from the crises years 2008 and 2011. Excluding these peaks, the average scale effect stood at about 0.25% of total costs.

Figure 2. Modified economies of scale and scale effect in euro area banks
(median)



Source: Author's calculations based on BankFocus data.

[29] The finding that smaller banks gain more from growing more is in line with Hughes and Mester (2013). Also, papers that did not include the COE usually found economies of scale only for smaller institutions (Hughes and Mester, 2013).

[30] Altunbas *et al*. (2001) found higher average return to scales for a sample of German banks between 1989 and 1996, standing at about 11%, even assuming a constant cost of equity.

Table 7. Modified economies of scale, by size and bank specialisation
(median by group)

	Size				Specialisation		
	Size 1	**Size 2**	**Size 3**	**Size 4**	**Commercial**	**Cooperative**	**Savings**
2006	1.13	1.12	1.11	1.10	1.10	1.11	1.10
2007	1.12	1.11	1.10	1.10	1.09	1.11	1.10
2008	1.12	1.11	1.10	1.10	1.10	1.11	1.10
2009	1.12	1.11	1.10	1.10	1.10	1.11	1.10
2010	1.11	1.10	1.09	1.09	1.09	1.10	1.10
2011	1.10	1.09	1.09	1.08	1.08	1.10	1.09
2012	1.10	1.09	1.09	1.08	1.08	1.09	1.09
2013	1.10	1.09	1.08	1.07	1.07	1.09	1.09
2014	1.09	1.08	1.07	1.06	1.07	1.08	1.08
2015	1.08	1.07	1.07	1.06	1.06	1.07	1.07
2016	1.07	1.07	1.06	1.06	1.05	1.06	1.07
2017	1.07	1.06	1.06	1.05	1.05	1.06	1.06

Note: The bank size is measured by the respective market share in the country of origin. Commercial, cooperative and saving banks are defined in Section 4.
Source: Author's calculations based on BankFocus data.

5.4. The equity effect

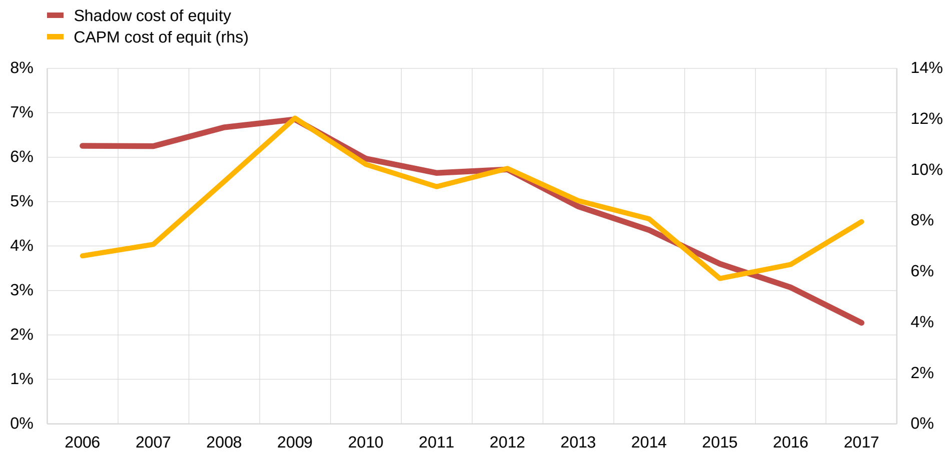
The equity effect captures the impact of the shadow cost of equity and changes in the equity ratio on Total Factor Productivity growth. It measures the impact of a change in equity on bank costs in a particular year. The shadow cost of equity (SCOE) is computed as the partial derivative of the cost function with respect to the equity ratio and shows the cost savings associated with an increase in the equity ratio.[31] Omitting the equity ratios from the cost function may result in biased efficiency estimates, since: *i*) Equity is a source of funding and should be considered a specific, quasi-fixed input; *ii*) The new regulatory regime requires higher capital requirements, influencing the production and cost profile of banks; and *iii*) Holding more equity could lead to lower total costs, as creditors could reward better capitalised banks by charging them less interest on other liabilities (therefore, this cost reduction should not be confused with technical efficiency; see Hughes *et al.*, 2001).[32] Other studies that include the equity ratio in the cost function are Maudos *et al.* (2002), Koetter and Poghosyan (2009), Fiordelisi *et al.* (2011) and Boucinha *et al.* (2012). On top of guaranteeing unbiased efficiency estimates, the SCOE is a useful indicator *per se*. This observation is especially important as the Capital Asset Pricing Model (Markowitz, 1952) requires market data for the calculation of the cost of equity, which are not available in the

[31] Hughes *et al.* (2001) emphasise that larger institutions tend to post a higher shadow cost of equity, potentially due to the under-utilisation of equity (*i.e.*, they post lower equity relative to its cost minimising value) as a result of safety nets, like deposit insurance schemes or too-big-to-fail.
[32] Altunbas *et al.* (1999 and 2007) and Altunbas *et al.* (2001) estimate a trans-log cost function for European and German banks, respectively, but omit equity from the estimated equation.

case of many banks. By contrast, the SCOE can be computed from standard bank data and the estimated trans-log cost function.

The shadow cost of equity and the cost of equity derived from the CAPM are presented in **Figure 3**. Our shadow cost of equity is comparable with results from the CAPM and points to a sharp increase after the start of the global financial crisis, peaking in 2009 at about 6.9% and decreasing afterwards, to 2.3% in 2017. These results suggest that the reward for being better capitalised increased in times of financial stress, but decreased afterwards, as equity ratios increased for euro area banks. The results for the overall level of the shadow cost of equity are in line with those found in the literature. For example, Shen *et al.* (2009) estimate a SCOE ranging from 2% to 6% for a sample of Asian countries, while Boucinha *et al.* (2009) estimate a SCOE ranging from 1% to 20% for Portuguese banks.

Figure 3. Shadow cost of equity and cost of equity derived from the CAPM
(weighted average)



Source: Author's calculations based on BankFocus data and Bloomberg (CAPM).

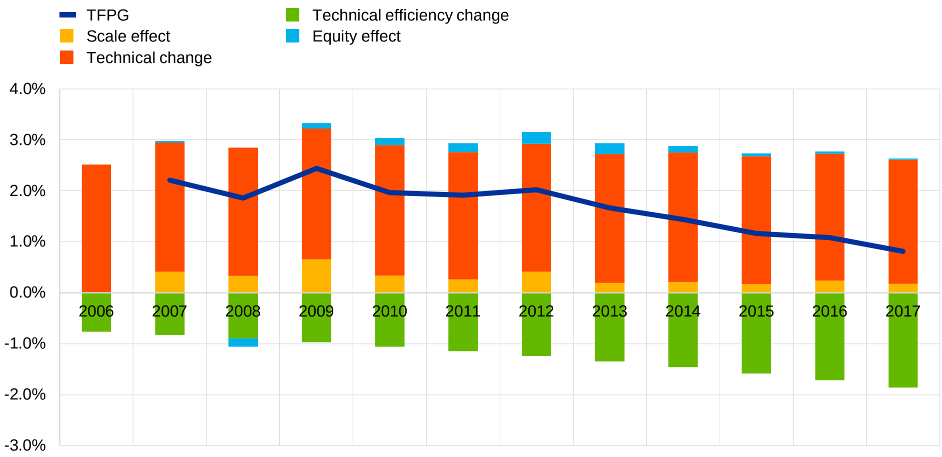
5.5. Total factor productivity growth

Having computed technical efficiency, technological progress, the equity and the scale effect, we are now able to compute the Total Factor Productivity growth of euro area banks based on Equation (1).

Results reported in **Figure 4** suggest that Total Factor Productivity of the median euro area bank grew at a rate of about 1.7% per year (on average) over the period between 2007 and 2017. However, Total Factor Productivity growth gradually decreased during this period, from above 2% in 2007 to below 1% in 2017. This result suggests that banks were able to generate the same amount of output with around 1% less costs per year in 2017, compared with 2% in 2007.

The largest component of Total Factor Productivity (in terms of absolute size) is technological progress. The contribution of this component remained fairly stable during the last ten years at around 2.5%. Technical efficiency change is the second largest component. Unlike technological progress, it exerts an increasingly negative impact on TFP (for the median bank, it decreased from -0.8% in 2006 to -1.95% in 2017). It is also noticeable that the scale effect always contributed to boost productivity in the banking sector, although to a lesser degree over time and the equity effect has become largely insignificant after 2013. Moreover, the gains from the scale and equity effects seemed always relatively small. All in all, these results suggest that Total Factor Productivity in the euro area banking sector has decreased over the last decade. This result is undesirable because euro area banks need to boost productivity in order to support much needed profitability.

Figure 4.Total factor productivity growth and components
(median)



Notes: Total Factor Productivity (TFP) is computed according to Equation (1).
Source: Author's calculations based on BankFocus data.

6. Conclusion

The analysis of efficiency in the euro area banking sector is very important for financial stability. In this regard, we contribute to the empirical literature by using an industrial organisation approach to compute Total Factor Productivity (TFP) growth in the euro area banking sector and decompose it into its main driving factors. In particular, we estimate a trans-log cost function to assess banks' relative ability to convert inputs into outputs, while minimising costs. The methodology is appealing because it allows the estimation of technical efficiency, technological progress and the equity and scale effects within the same econometric framework. To the knowledge of the authors, this is the first study that disentangles permanent and time-varying inefficiency in the euro area banking sector. The distinction is very important because lack of distinction may lead to biased estimates of efficiency and because the set of policies needed in both cases is completely different.

Overall cost efficiency in the euro area banking sector amounted to around 84% (on average) over the period, suggesting that the median bank needs around 16% more resources compared with the most efficient bank in the sector. These results are in line with other recent research in this field. The largest part of bank inefficiencies stems from structural long-term factors (such as location, client structure, macroeconomic environment, regulation, etc.) which have a bigger impact on bank efficiency than time-varying factors. Therefore, structural policies aimed at improving persistent efficiency of the euro area banking sector should be considered. Finally, our results regarding efficiency suggest that more efficient banks tend to record lower average costs, lower cost-to-income ratios, higher profitability, lower size (by market share), lower credit risk ratios and tend to be better capitalised institutions.

Technical efficiency is however only one of the components of bank productivity, together with technological progress, the equity effect and economies of scale. On average over the period, the rate of technological progress for the median euro area bank amounted to 2.5%. Moreover, estimations for the shadow cost of equity are comparable to results from the CAPM and show a sharp increase after the start of the global financial crisis (at about 6.9% in 2009), suggesting that the reward for being better capitalised increased in times of financial stress. Regarding economies of scale, we find that they tend to be larger for the smaller institutions, although the largest institutions also experience economies of scale. For the median euro area bank, they stood at around 9% on average over the period.

Combining all the components together we observe that Total Factor Productivity in the euro area banking sector has decreased over the last decade (from above 2.0% in 2007 to 0.8% in 2017). This result is undesirable given the need to boost productivity in euro area banks in order to support much needed profitability. This unfavourable situation for the euro area banking sector is leading to changes in bank's behaviour, mainly through rationalisation of branches and staff, together with digitalisation of the business process and mergers and acquisitions both within countries and at the euro area level (to achieve economies of scope and scale).[33] However, it might take some time until this cost cutting activities bear fruits.

[33] On M&A developments in the euro area see ECB (2017).

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