Adjustment costs in the technical efficiency: an application to global banking.

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Abstract

This paper proposes a new framework of measuring technical efficiency that takes into account adjustment costs in variable inputs associated with changes in efficiency. We look closely at the implicit assumption in any model of technical efficiency that inputs could freely adjust. Yet, the technical efficiency is determined from the allocation of inputs by the firm to production on the one hand and to efficiency on the other. We show that technical efficiency depends on adjustment costs in variable inputs. Estimating the proposed model has certain complexities that we overcome by employing a non-parametric Local Linear Maximum Likelihood (LLML). In the empirical section, we employ a comprehensive global banking sample and estimate bank alternative profit efficiency across a plethora of countries with strong variability in the underlying adjustment costs. Moreover, given the observed heterogeneity across countries evidence shows that adjustment costs due to personnel expenses are the highest among advanced countries. Emerging economies show strong potential in terms of efficiency post-financial crisis, mainly due to lower labor adjustment costs. Alas, our findings show some persistence in adjustment costs post the financial crisis.

Keywords: Technical efficiency, adjustment costs, non-parametric Local Linear Maximum Likelihood, global banking.

JEL classifications: D24, G2, G21, G33.

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1. Introduction

In this paper we argue that efficiency measurement should take into account the existence of adjustment costs related to changes variable inputs. This is of particular importance in the aftermath of the financial crisis due to dramatic changes in the underlying structural conditions of financial markets. Yet, the literature to this day in all models of technical efficiency remains agnostic regarding the dependency of technical efficiency to adjustment costs in variable inputs. The norm in the literature (Koutsomanoli-Filippaki and Mamatzakis, 2009; Lozano-Vivas A. and Pasiouras F., 2010; Koutsomanoli-Filippaki and Mamatzakis, 2011; Tzeremes, 2015; Tsionas 2015; Bolta and Humphrey, 2015; Galán et al. 2015;) is to assume that adjustment costs in variable inputs are not significant. However, the technical efficiency is determined from the allocation of inputs by the bank to production on the one hand and to efficiency on the other. The process of this allocation is bound to generate adjustment costs, as variable inputs cannot instantaneously change without some loss in efficiency. In this paper, we propose a model that relaxes the assumption of no adjustment costs and as such we measure this adjustment process of technical efficiency.

Despite the importance of correctly measuring technical efficiency and its underlying adjustment costs there is limited evidence (Tsionas, 2006; Kien and Tsionas, 2016; Tsionas, 2016). There is, of course, an extensive literature on bank efficiency (Altunbas et al., 2001; Koutsomanoli-Filippaki and Mamatzakis, 2009; Lozano-Vivas A., Pasiouras F., 2010; Koutsomanoli-Filippaki and Mamatzakis, 2011; Bolta and

Humphrey, 2015; Galán et al. 2015) that this paper relates to. A common finding of the literature is the high level of cross-country heterogeneity in the global banking industry, (i.e. Altunbas et al., 2001; Lozano-Vivas A., Pasiouras F., 2010; Koutsomanoli-Filippaki and Mamatzakis, 2011; Bolta and Humphrey, 2015; Galán et al. 2015).[1] Tsionas (2006) show that the variability in bank efficiency in US could be explained by adjustment costs. The author argues that efficiency levels across banks would not homogenously adjust in the short run, as there is some persistence due to heterogeneity in their adjustment costs. We follow Tsionas (2006) lead and herein we closely look at the underlying reasons for any persistence in efficiency by proposing a way to estimate adjustment costs in variable inputs at a global level that would reveal possible variability in efficiency. [2]

Moreover, the starting point of our model is the simple observation that the adjustment of technical efficiency for a firm indeed comes at a cost due to changes both in efficiency and in inputs. We provide a non-parametric model that measures such costs. Modeling adjustment costs in technical efficiency comes with some cumbersome estimations implications. To overcome such difficulties we propose to employ a non-parametric likelihood estimation method, opting for Local Linear

[1] The literature on bank efficiency is quite vast. A starting point could be traced back to Berger and Mester, (1997), that seemed to spark various studies thereafter (see for example for European banks, Koutsomanoli-Filippaki and Mamatzakis, 2009; Koutsomanoli-Filippaki and Mamatzakis, 2011; whereas for transition economies see Mamatzakis, (2009), Tsionas et al., (2015), Gahan et al. (2015) and for the US banking see Tsionas (2015). It is evident that most of the empirical studies focus on advanced economies and it is not common examine bank efficiency at a global level. This paper fills this gap in the literature in the empirical application section.

[2] Galán et al. (2015) argue that there are costs, for Colombian banks, associated with instant adjustment that would cause inefficiency. The authors extend Tsionas (2006) and report efficiency heterogeneity across Colombian banks based on size, ownership and corporate structure.

Maximum Likelihood (LLML) in an initial conversion.[3] This LLML allows estimating all adjustment costs of technical efficiency for all banks in our global sample over time.

We employ a global banking sample as our new proposed methodology provides a way for taking into account adjustment costs in alternative profit efficiency, due to variable inputs, irrespectively of the intrinsic characteristics of financial markets. The coverage of the global bank sample is of importance as financial markets, and in particular the banking industry, have been through a remarkable restructuring process, partly because of the financial crisis in 2008 and partly because changes in their underlying productive structure so as to become more efficient. Undoubtedly, adjustment costs play an important role in the restructuring process of the banking industry. Yet, despite the restructuring steps observed in the banking industry, with some variability, across the world the underlying bank adjustment costs have not been quantified to date. Nevertheless, it is well documented (Demirguc-Kunt and Huizinga, 2010; Mamatzakis et al. 2015; Galán et al., 2015) that banks, since the financial crisis, have targeted operating costs, for example cutting down personnel expenses, aiming to improve their operating performance.[4] The financial crisis has had a cataclysmic impact in rationalizing and scaling down operating expenses as it provided the opportunity step ahead restructuring efforts. In this paper, we argue that bank

[3]Henderson and Parmeter (2009) provide a survey of regressions with references to the underlying constraints (see also Kumbhakar et al. 2007; Kumbhakar and Tsionas, 2010).

[4] In the aftermath of the crisis, questions emerged on what went wrong and how it could be corrected. Much of the attention has focused on the structural reforms needed to restore efficiency in the banking industry. Such voices of bank restructuring across operating costs, and in particular personnel expenses, have not been new as there were present well before the financial crisis (Koutsomanoli-Filippaki and Mamatzakis, 2009; Koutsomanoli-Filippaki and Mamatzakis, 2011). However, the crisis revealed that the warranted structural reforms were delayed, and certainly had not been carried out during good times (Mamatzakis et al. 2015; Galán et al., 2015). The outcome is higher adjustment costs in the aftermath of the crisis as we demonstrate.

efficiency might have improved across the world since the crisis, and in particular in recent years, but as adjustment costs are also present such improvement is impeded. Moreover, results show that bank alternative profit efficiency has been subdued during the financial crisis in 2008 and 2009. But, there was a decline in bank alternative profit efficiency in advanced economies well before the financial crisis. Since the financial crisis, there has been a remarkable recovery of efficiency across the world, and in particular in emerging economies as they have managed to exceed their pro-crisis efficiency threshold. Therefore, the recovery in bank profit efficiency since the financial crisis across the world has not been homogenous. We show that adjustment costs in variable bank inputs, in particular the labour input, could explain the observed heterogeneity in bank profit efficiency across the world since the financial crisis.

Thereby, this paper contributes to the existing literature in several ways. Firstly, from a methodological point of view, we propose a new model of bank efficiency that decomposes adjustment costs in variable inputs. Secondly, we focus on global bank alternative profit efficiency, aiming to examine cross-country variability in the underlying efficiency adjustment costs. Thirdly, we examine the underlying relationship between those adjustment costs prior and ex-post to the financial crisis. Overall, our results reveal striking variability in adjustment costs of alternative profit efficiency across countries, as well as over time. It is worth noticing that higher adjustment costs appear to persist in 2011 and 2012, that is well after the financial crisis, suggesting that improvements in bank efficiency world wide is impended by such persistence.

The rest of the paper is structured as follows. Section 2 develops our new model of efficiency. Section 3 describes the global data set, whilst section 4 discusses our results. Section 5 offers some conclusions.

2. A new model for bank efficiency

Following Tsionas (2006) who argues that there is persistence in efficiency for US banks, we propose a technical efficiency model that permits searching for underlying causes of such persistence. Moreover, the implicit assumption in any model of efficiency is that inputs could freely adjust. The standard assumption in the literature (see Koutsomanoli-Filippaki and Mamatzakis, 2009; Koutsomanoli-Filippaki and Mamatzakis, 2011; Galán et al. 2015; Kien and Tsiona, 2016; Tsionas, 2016) is that the efficiency is determined from the allocation of inputs by the firm to production on the one hand and efficiency on the other. This allocation implies that efficiency cannot be adjusted without adjustment cost and, therefore, any change in efficiency would require the use of resources. Therefore, the adjustment costs should be taken into account. Such adjustment costs we argue here depend on changes in variable inputs. This dependence is that, in the input-output space, the level of efficiency really depends on the use of inputs and the capacity to produce output(s).

2.1 The bank optimisation problem: revisited

In detail, given a production function $y = f(x)e^{-u(x)}$, inefficiency is given by the function $u:\mathbb{R}_{+}^{K} \to \mathbb{R}_{+}$, which is assumed twice differentiable.[5] The cost minimization problem becomes:

$$C(w,y) = \min_{x\hat{I}R_{+}^{k}}: w'x, \text{ s.t. } y \le f(x)e^{-u(x;z)}. \tag{1}$$

The inefficiency function depends also on control variables $z \in R^{m}$ but we omit this dependence in what follows, for simplicity. The first order conditions to the problem are:

$$\begin{aligned} \frac{w_k}{w_1} &= \frac{f_k(x) - f(x)u_k(x)}{f_1(x) - f(x)u_1(x)}, k = 2,...,K, \\ y &= f(x)e^{-u(x)}, \end{aligned} \tag{2}$$

where $f_k(x) = \frac{\partial f(x)}{\partial x_k}, u_k(x) = \frac{\partial u(x)}{\partial x_k}, k = 1,...,K.$

In alternative form we have the conditions:

$$\frac{s_k}{s_1} = \frac{\frac{\partial \log f(x)}{\partial \log x_k} - u(x)\frac{\partial \log u(x)}{\partial \log x_k}}{\frac{\partial \log f(x)}{\partial \log x_1} - u(x)\frac{\partial \log u(x)}{\partial \log x_1}}, k = 2,...,K, \tag{3}$$

$$y = f(x)e^{-u(x)},$$

where $s_k = \frac{w_k x_k}{C}, k = 1,...,K$ are cost shares.

To simplify notation, define the elasticities:

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5 For simplifying the analysis we would refer to inefficiency.

$$\varepsilon_k^f = \frac{\partial \log f(x)}{\partial \log x_k},\ \ \varepsilon_k^u = \frac{\partial \log u(x)}{\partial \log x_k},\ \ (4)$$

to obtain:

$$\begin{gathered}\frac{s_k}{s_1} = \frac{\varepsilon_k^f(x) - u(x)\varepsilon_k^u(x)}{\varepsilon_1^f(x) - u(x)\varepsilon_1^u(x)}, k = 2, \ldots, K, \\ y = f(x)e^{-u(x)}.\end{gathered} \quad (5)$$

Using logs we have:

$$\begin{gathered}y = F(x) - u(x) + v_1, \\ \log\left(s_k / s_1\right) = \log\left\{\varepsilon_k^f(x) - u(x)\varepsilon_k^u(x)\right\} - \log\left\{\varepsilon_1^f(x) - u(x)\varepsilon_1^u(x)\right\} + v_k, k = 2, \ldots, K,\end{gathered} \quad (6)$$

assuming y is redefined to be in logs, $F(x) = \log f(x)$, $v_1, \ldots, v_k$ are error terms, provided, of course, that:

$$\varepsilon_k^f(x) - u(x)\varepsilon_k^u(x) > 0, k = 1, \ldots, K.\ \ (7)$$

In the system of equations (6), the endogenous variables are the x's. We can easily generalize to multi-output production provided we have an output distance function as:

$$y_1 = F(x, \tilde{y}_{-1}) - u(x),\ (8)$$

instead of the first equation in (6), where outputs are $y_1, \ldots, y_M$ and $\tilde{y}_{-1} = \left[y_2 - y_1, \ldots, y_M - y_1\right]$. At this point it is useful to assume that all x's and y's are, in fact, defined in log terms and the vector x contains $\tilde{y}_{-1}$ as well. For the output distance function we assume a translog form:

$$F(x) = \beta_0 + \beta' x + \tfrac{1}{2} x' B x. \quad (9)$$

The function u(x) is assumed unknown. Information about u(x) is provided by the output distance function and the first order conditions in (6) where its elasticities are involved. Our strategy is to estimate non-parametrically the system in (6) and obtain the unknown function u(x) subject to the constraint $u(x) \geq 0$ as well as the elasticities $\varepsilon_k^u, k = 1,\ldots,K$ allowing for the endogeneity of x's.

2.2 A non-parametric estimation of efficiency

To proceed with the nonparametric estimation consider the Jacobian of transformation from v to x in (6) as:[6]

$$\mathcal{J}(x) = \left\| \begin{array}{c} -\nabla f(x)' + \nabla g(x)' \\ -\left[I_{J-1} \otimes A(x) \right]^{-1} \nabla A(x) + A_1(x) \nabla A_1(x) \\ \end{array} \right\|, \quad (10)$$

where $A(x) = [A_1(x),\ldots,A_K(x)]'$, $A_k(x) \triangleq \varepsilon_k^f(x) - u(x)\varepsilon_k^u(x), k = 1,\ldots,K.$

Given the translog specification we have:

$$\nabla f(x) = \beta + Bx \,. \quad (11)$$

However, the other expressions in (10) are complicated as the function u(x), and therefore its derivatives, are unknown. To proceed, we define the vector of residuals from (6):

[6] Kumbhakar and Tsionas (2010) provide some insights over the advantages of nonparametric estimation, whereas Kumbhakar et al. (2007) propose a local maximum likelihood approach for nonparametric stochastic frontiers.

$$
\begin{aligned}
&\mathrm{V}_{\mathrm{it},1}(\theta) = \mathrm{y} - \mathrm{F}(\mathrm{x}_{\mathrm{it}}) + \mathrm{u}(\mathrm{x}_{\mathrm{it}}),\\
&\mathrm{V}_{\mathrm{it,k}}(\theta) = \log\left(\mathrm{s}_{\mathrm{it,k}} / \mathrm{s}_{\mathrm{it},1}\right) - \log\left\{\varepsilon^{\mathrm{f}}_{\mathrm{k}}(\mathrm{x}_{\mathrm{it}}) - \mathrm{u}(\mathrm{x}_{\mathrm{it}})\varepsilon^{\mathrm{u}}_{\mathrm{k}}(\mathrm{x}_{\mathrm{it}})\right\} + \log\left\{\varepsilon^{\mathrm{f}}_{1}(\mathrm{x}_{\mathrm{it}}) - \mathrm{u}(\mathrm{x}_{\mathrm{it}})\varepsilon^{\mathrm{u}}_{1}(\mathrm{x}_{\mathrm{it}})\right\}, \mathrm{k} = 2,\ldots,\mathrm{K},
\end{aligned}
\tag{12}
$$

Let us suppose for the sake of simplicity in presentation that $v_{it} \sim i.i.d.N_J(0,\Sigma)$. Then the parametric likelihood of (6) if we knew the functional forms would have been given by the following:

$$
L = (2\pi)^{-nTK/2} \,|\,\Sigma\,|^{-nT/2} \prod_{i=1}^{n}\prod_{t=1}^{T} J_{it}(\theta) \exp\left\{-\tfrac{1}{2}\sum_{i=1}^{n}\sum_{t=1}^{T} V_{it}(\theta)'\Sigma^{-1}V_{it}(\theta)\right\}, \tag{13}
$$

where indices i,t stand for individual banks and time respectively.

Of course, as the functional forms are unknown, the parametric likelihood is not feasible. We use, instead, the method of Local Linear Maximum Likelihood (LLML) to convert (13) to a non-parametric likelihood. In the method of LLML we specify the u(x) function as follows:

$$
\log u(x_{it};\alpha) = \alpha_o + \alpha'(x - x_{it}), \tag{14}
$$

where α_o is a constant and $\alpha \in \mathbb{R}^K$ is a parameter vector.

To avoid the normality assumption we introduce heteroskedasticity of unknown form as follows.[7] Given the Cholesky decomposition $\Sigma(x) = H(x)'H(x)$ we assume that each element of $H(x)$, denoted by $h_s(x), s = 1,\ldots,\frac{K(K+1)}{2}$, has the following representation:

[7] The control variables in z do not enter into the determination of Σ(x). However, they enter non-parametrically into the inefficiency function, u(x).

$$h_s(x, x_{it}; \alpha) = \alpha_{os} + \alpha'_{(h),s}(x - x_{it}),\ s = 1, \ldots, \tfrac{K(K+1)}{2}, \qquad (15)$$

where α_{os} is a constant and $\alpha_{(h),s} \in \mathbb{R}^K$ are parameter vectors.

We denote the entire vector of local parameters by α. Given these specifications the conditional local log likelihood function for the linear local fit at x is defined as follows:

$$\begin{aligned} &\log L_x(\alpha) = \sum_{i=1}^{n} \sum_{t=1}^{T} l_{it}(\alpha); \\ &l_{it}(\alpha) = \left\{ -\tfrac{1}{2}\log|\Sigma(x - x_{it}; \alpha)| - \tfrac{1}{2} V'_{it}(\theta)\Sigma(x - x_{it}; \alpha)^{-1} V_{it}(\theta) + \log\left\| J_{it}(\theta) \right\| \right\} \cdot K_B(x - x_{it}), \end{aligned} \qquad (16)$$

where $K_B(z)$ is a kernel function.

We, therefore, choose the following kernel function:

$$K_B(z) = |B|^{-1} K(B^{-1}z), \quad (17)$$

where B is a bandwidth matrix.

For the kernel function we assume:

$$\int K(z)dz = 1, \int ZZ' K(z)dz = m_2 I, \quad (18)$$

for some positive constant m_2.

The kernel function is derived as a product of univariate kernels along the lines of Kumbhakar et al. (2007, section 2.3). Specifically, we opt for:

$$K(z) = \prod_{j=1}^{D} K_o(z_j), \quad (19)$$

where $K_o(u)$ is a symmetric univariate probability function (the standard normal in our case) and D denotes the dimensionality.

In this case

$$\int ZZ' K(z)dz = \left(\int z_o^2 K_o(z_o) dz_o \right) I_D. \quad (20)$$

Thus, the log likelihood in (13) can be maximized using standard numerical optimization techniques to yield local linear estimates $\hat{\alpha}(x_{it})$. The local linear estimator at x is $\hat{\alpha}_o(x)$ where $\hat{\alpha}(x)$ maximizes (13).[8]

4. Data and Variables

We start the construction of our sample by including all the countries and thereby the corresponding banks available in the Bankscope database.[9] Our final sample is an unbalanced dataset that includes 17399 observations for 31 advanced countries, 7130

[8] The asymptotics of the estimator under general regularity conditions are provided in Theorem 2.2 of Kumbhakar et al. (2007). Initial conditions are chosen as described in section 3.1 of Kumbhakar et al. (2007) in connection to Gozalo and Linton (2000). We used the FilterSD software which is written in Fortran77.

[9] We exclude banks for which: (i) we had less than three observations over time; (ii) we had no information on the country-level control variables; (iii) we had no information of nonperforming loans.

observations for 35 emerging countries, and 2471 observations for 40 developing countries. Our sample covers the period from 2000 to 2013. The classification of country-groups is based on IMF's World Economic Outlook (2015). All the bank-specific financial variables are obtained from Bankscope database, in thousand US $. Data for country-level variables are collected from the World Bank Indicators database.

We follow the alternative profit function approach (Berger and Mester, 1997, and Berger and Mester, 2003). As in the empirical application we employ a global sample, the alternative profit function is appropriate because it would consider the different degree of competition across bank industries, whilst it also takes into account the effect of quality of outputs on revenues and costs. In addition, during the sample period the financial crisis took place, and the alternative profit efficiency would sufficiently captures any diversity in responses by banks to the crisis.[10]

Thus, we measure the alternative profit as $ln(\Pi + |\Pi_{min}| + 1)$, where profits is Π and minimum profits $|\Pi_{min}|$. Adding the absolute minimum profit and one to profit ensures that we have positive values. We include three bank outputs: net loans (y_1), other earning assets (y_2), and off balance sheet items (y_3). There are three input prices: price of fund (w_1) is the ratio of total interest expenses to total customer deposits; price of physical capital (w_2) is defined as other operating expenses over fixed assets; and price of labour (w_3) is calculated as personnel expenses divided by total assets. Equity (E) is included as a netput (Berger and Mester, 1997), and nonperforming loans (NPL)

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[10] The alternative profit would be the dependent variable in our framework and replaces the cost.

is considered as a negative quasi-fixed input (Hughes and Mester, 2010). The summary statistics of these variables are provided in Table 1 for each country-group. Interestingly, we notice that the average amount of nonperforming loans in advanced economies' banking industries is almost twice that in emerging economies and eight times that in developing economies.

[INSERT TABLE 1 ABOUT HERE]

Given that during the period of our sample there have been episodes of high risk, we take into bank-specific risk in the estimation of the efficiency scores. To this end, we opt for the z-score as a measure of insolvency risk at bank level. This is defined as z-score= (1+ ROE)/σ_{ROE}, where ROE is the return on equity and σ_{ROE} is the estimate of standard deviation of ROE. In addition, to take into account of liquidity risk we employ the ratio of liquid assets over total assets.[11] Lastly, we also use the ratio of equity over total assets to take into account capital risk (Athanasoglou et al., 2008; Lepetit et al., 2008). High capital ratio would imply low capital risk, i.e. equity is a buffer against financial instability. Table 1 includes some descriptive statistics of the three measures of bank risk employed in our analysis. Perhaps not surprisingly, given the financial crisis in 2008, banks in the advanced economies, as z-score at 0.69, face higher risk compared to emerging and developing, 0.8081 and 0.8443 respectively. Descriptive statistics also show that banks in emerging and developing countries are more capitalized and have more liquidity than banks in advanced economies.

[11] Liquid assets are the sum of trading assets, loans and advances with maturity less than three months. Liquidity ratio reports bank's liquid assets. If the ratio takes low values would imply high liquidity risk.

To capture other potential determinants of efficiency, we use a number of bank-specific and country-level control variables. Table 1 reports country-group averages of the control variables. With regard to the bank-specific variables, we use the natural logarithm of total assets to proxy for the size of banks (Galán et al., 2015). We further employ a non-interest income ratio, estimated by the sum of the net fees and commissions over total assets, and securities over total assets ratio to proxy or the non-lending activities of banks.[12] Moreover, we control for the impact of financial conditions and include a crisis dummy that takes the value of 1 for the 2007-2009 years, and 0 otherwise. Following a number of cross-country studies that examine bank performance (Barth et al., 2004; Galán et al., 2015; Tzeremes, 2015), we also account for cross-country differences in macroeconomic and structural conditions. To control for the general level of economic development, we use real GDP per capita. We also use inflation to capture the monetary stance and the value of total shares traded on the stock market exchange to control for the market size of an economy. Lastly, we use population density in order to proxy for the demand density in each country.[13]

[12] Lozano-Vivas and Pasiouras (2010) opt for non-interest income and off balance sheet (OBL) items as additional bank outputs for a global sample. Their results show some variability, as the inclusion of OBS has no statistical significant effect on efficiency, whereas non-interest income has some significant effect. However, the authors demonstrate that the inclusion of these additional bank outputs would not affect the direction of the impact of the main determinants of efficiency.

[13] In recent years there is a strand of literature that highlights issues related to the impact of regulation on bank efficiency. Gaganis and Pasiouras (2013), and Mamatzakis et al. (2015) provide evidence that regulation at the country level could affect bank efficiency. Bank regulation and bank supervision is an important topic that would warrant further investigation, also in light of the fact that such regulation is very defragmented, not only at a global level, but also within currency unions such as the euro area. Only in recent year there is some progress to a unified bank supervision framework in the euro area with the ambition to become a banking union. The defragmentation of bank regulation across the world poses challenges, as there is not a widely accepted way of counting for bank regulation, in the econometric estimation of bank efficiency. Some indexes that capture bank regulation have been proposed, for example indexes of the Heritage Foundation. The drawback of opting for such indexes is that they show very limited time variability as they are based on survey data that are not annually revised. As the aim of the present study is to study adjustment costs that are observed in the short term and are time varying, introducing variables that are mainly of long-term nature would not benefit our analysis.

5. EMPIRICAL RESULTS

The Local Linear Maximum Likelihood that we propose in log likelihood (13) has the main advantage that it provides a fit for every observation in the sample, whilst we can also compute, numerically, elasticities of the form of Equations (2) and (3). This is, in fact, a great advantage over parametric procedures.

Before proceeding with the results note that regarding bandwidth selection, we choose $B = b \cdot I_D$ where the vector $b = b_o S_x (nT)^{-1/5}$ and S_x is the vector of sample standard deviations of the covariates and b_o is a constant. Therefore, the bandwidth is adjusted for different scales of the variables and different sample sizes. To choose the value of b_o we use cross-validation as in section 3.2 of Kumbhakar et al. (2007). As the sample size is quite large we leave out 10% of the observations randomly for a total of 50 times and for a grid of 20 values of b_o. Our final optimal value for this parameter was 1.70, 2.20 and 1.55 for the three data sets.

5.1 Alternative Bank Profit efficiency across the world

Figure 1 shows the alternative profit efficiency over time for each country-group that is: advanced, emerging and developing economies. There is a pick in the efficiency in 2006 in the advanced economies that reached 0.88, and then a sluggish performance till 2008 where a sharp decline in bank efficiency is reported. The pick in efficiency in developing economies is recorded in 2006 at 0.80, whilst the pick in emerging economies comes a year earlier in 2005. It is interesting that in 2006 and 2007 the alternative profit efficiency is higher in developing economies compared to emerging. However, whereas in emerging economies the efficiency score holds somewhat since 2007 and during the period of the crisis, efficiency in developing economies continue to decline at much faster rate.[14] Thus, since the crisis efficiency in developing economies is lagging both advance and emerging economies. Alas, our results reveal that alternative profit efficiency drops across the world as early as in 2005. These results are of some significance as the financial crisis is mostly documented to take effect in 2008 and 2009. Our results show that declining bank efficiency across the world did raise early warning signals of the forthcoming financial crisis. Yet these early signals have been ignored.

The Figure 1 shows that bank efficiency scores reached the lowest point in 2009. Thereafter, there has been a steady and remarkable recovery of bank efficiency across the world. Notably, there is a striking recovery in bank efficiency of emerging economies, well above the pro-crisis threshold, since 2009. During the same period, banks in advanced and developing economies also register improvements in efficiency. Clearly, there is heterogeneity in the recovery of bank efficiency across the world. Bank efficiency in emerging economies has exhibited strong resilience and less

[14] The strong performance of the banking industry prior to the financial crisis has been documented. For example, Backé and Wójcik (2013) report evidence of high performance due to strong credit expansion in the Central and Eastern European economies between 2004 and 2006. Similarly, Hume and Sentance (2009) find that there was a sharp rise in bank lending in advanced and emerging countries till 2006. Around this period, in the developing world countries such as China and India stepped forward with some unprecedented growth performance that has led to an increase in living standards and as a consequence in the advancement of financial industry, and in particular the banking industry.

affected by the financial crisis compared to developing and advanced economies.[15] The question that now emerges is whether adjustment costs in variable inputs could provide an explanation regarding the observed heterogeneity in bank efficiency across the world since the financial crisis?

[INSERT FIGURE 2 ABOUT HERE]

Figure 2 augments the findings of Figure 1 and presents the density functions of bank alternative profit efficiency for the three groups of our global bank sample. The density functions reveal some tail effects across all groups, in particular in advanced and emerging economies. Moreover, the densities show evidence of non-normality with the density of developing economies being bimodal, revealing the presence of at least two sub-groups.[16] The positive skewness of the density in advanced economies may also indicate multiple groups with about the same means but different variances.

[INSERT FIGURE 2 ABOUT HERE]

In Table 2 we present the alternative profit bank efficiency scores per country in advanced economies. Among 31 advanced economies, banks in Portugal and Greece

[15] Although to the best of our knowledge there is no study that applies a global sample, there are some recent studies for emerging economies (Galán et al. 2015; Tzeremes, 2015) that report upwards trends in efficiency.

[16] In what follows we are focusing in much more detail in the heterogeneity of efficiency scores across countries in the emerging economies. However, it is worth emphasizing that this bimodal density function clearly indicates two unequal modes, a small and a large one, with two different means and variances.

are the least efficient with average efficiency at 0.71.[17] On the other hand banks in Australia, UK, Belgium, Germany, Denmark and the US show strong performance around 0.92. Our finding for US banks supports the results of Tsionas (2015). Similarly, strong bank performers at around 0.85 are Austria, Canada, Czech Republic, France, Israel, Japan, New Zealand, Singapore, and Switzerland.

[INSERT TABLE 2 ABOUT HERE]

Table 3 reports the alternative profit bank efficiency per country in emerging economies. The disparity between bank efficiency in emerging countries is larger than that in advanced countries. There is a blend of geographic regions in this group, comprising of 35 countries. The lowest score, by far, of bank alternative profit is reported for Namibia at 0.55, with the highest score reported for Philippines at 0.91. Banks in South Africa, Thailand and Qatar also exhibit strong performance with an average efficiency at 0.87. In parallel, banks in China and India also exhibit strong performance at 0.83, in line with Tzeremes (2015). Our efficiency score for Colombian banks is similar to the findings in Gahan et al. (2015) though somewhat lower. Athanasoglou, et al. (2008) show that financial liberalisation in Hungary, Poland, and Romania has led to improvements in their bank efficiency in the first part of 2000s. The present study reports also bank efficiency scores of around 0.8 for those countries. In fact, for many economies in emerging group a common denominator has been the process of financial integration and liberalisation. This could help explain strong bank efficiency in emerging economies.

[INSERT TABLE 3 ABOUT HERE]

[17] Bank efficiency scores for European countries are broadly in line with previous findings in the literature (see Koutsomanoli-Filippaki and Mamatzakis, 2009), though the present findings are somewhat at the low end of the former.

Lastly, Table 4 shows significant variability in bank alternative profit efficiency across developing countries. For example, banking industry in Botswana, Cambodia and Ethiopia appear to be much less efficient, at an average bank efficiency level of around 0.55, compared to other countries in this group. The highest efficiency is reported for banks in Jordan at 0.9, followed by banks in Andorra and Croatia.

[INSERT TABLE 4 ABOUT HERE]

For purpose of comparison, we have also estimate the bank profit efficiency for each country according to geographic region.[18] Results appear to be similar to the ones reported above. Amongst six regions, banks in Europe, in Japan and in USA are the most efficient with an average efficiency of 0.88.

5.2. Adjustment costs in funds (F), physical capital (K) and labour (L).

The main message we extract from Figure 1 is that efficiency in advanced and developing economies is losing dynamism if compared to emerging economies in recent years that is during the post financial crisis period. Herein we report the adjustment costs in efficiency due to funds, physical capital and labour (see Table 5)

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[18] The classification follows the one proposed by IMF World Economic Outlook. Moreover, to safeguard that there is not a sample selection bias in the efficiency scores across countries we follow the geographical classification of IMF as: Europe, Latin America and the Caribbean, Asia/Pacific Middle East, North Africa, Afghanistan, and Pakistan, Commonwealth of Independent States, and Sub-Saharan Africa. The range of bank average efficiency across the world is similar to the results reported herein and in average there is a variation between 0.6 and 0.9, except for some sub Saharan countries where very low bank efficiency scores are reported. Results are available under request.

for each country-group. Adjustment costs are measured in terms of percentage change in bank profit efficiency due to percentage changes in variable bank inputs.

Overall, the reported adjustment costs satisfy the monotonic condition and linear homogeneity constraints of the alternative profit function. Table 5 reports these adjustment costs in terms of percentage changes in alternative profit efficiency due tp variable inputs changes. Moreover, the results show that the adjustment cost in funds is the largest in magnitude across the world, whereas it reaches its highest level for developing economies at -0.52%, whereas it is -0.43% and -0.46% for advanced and developing countries respectively. The adjustment cost for funds in developing economies, for example, implies that a one % increase in adjustment cost in funds will reduce bank profit efficiency by -0.52 %. This finding is of some economic significance as the bank profit efficiency scores in developing economies is clearly lagging behind the bank profit efficiency in advanced and emerging economies. The high adjustment cost of funds would explain this sluggish performance, in particular during the post financial crisis period. The financial crisis appears to trigger higher adjustment costs in developing economies that surges and persists post the financial crisis in the period from 2011 to 2013.

[INSERT TABLE 5 ABOUT HERE]

In general, the average adjustment cost of physical capital in advanced economies at -0.15% is the lowest across the three groups of economies. However, the adjustment cost of labour in advanced economies at -0.41% in the period 2008 to 2010 is quite high. It is equally worrying that there is persistence in adjustment costs for labour in advanced economies at -0.33% in the period 2011 to 2013, higher than that of emerging and developing economies Our results show that the restructuring of banking industries in advanced economies ought to focus on personnel expenses, given that the underlying adjustment cost in labour appears to weight upon efficiency much more than the adjustment costs in funds and capital. On the other hand, lower adjustment costs in labour in emerging economies appear to boost their bank profit efficiency post financial crisis. Overall, the adjustment costs in emerging economies explain the strong trend in profit efficiency post the financial crisis, as they have lower adjustment costs for physical capital and funds compared to developing economies, and lower adjustment costs of labour compared to advanced countries.

The reported adjustment costs in variable inputs raise some concerns as high adjustment costs persist well after the financial crisis. Note, though, that adjustment costs decline in 2013. To clarify this point further Table 5 reports adjustment costs for the three main sub-periods of our sample: 2000 to 2007 (the pro crisis period), 2008 to 2010 (the crisis period), and finally 2011 to 2013 (the post crisis period). Clearly, adjustment costs across all three bank variable inputs increased across the world during the crisis period. The highest adjustment cost is reported for funds across the world in the period 2008 to 2010, but also during the post financial crisis period. This may not come as a surprise as the financial crisis exposed a serious depletion of capital and thereby liquidity crisis. This development clearly undermined the recovery in the bank profit efficiency across the world. In developing economies there is strong persistence in adjustment costs in funds and labour during the post financial crisis period that is in contrast with the trend in emerging and advanced economies. This persistence in adjustment costs could explain why bank profit efficiency recovery in developing economies is lagging behind during the post financial crisis period.

Moreover, Figure 3 shows the adjustment cost for capital, labour and funds across countries. It demonstrates further that in advanced economies labour adjustment costs sway substantially upon profit efficiency compared to adjustment costs in emerging and developing economies. On the other hand, the adjustment costs in funds continue to play the dominant role in developing economies, and to less extend in emerging economies in recent years.

[INSERT FIGURE 3 ABOUT HERE]

5.3. The effect of control variables on alternative bank profit efficiency.

We turn next our attention of the impact of bank risk and control variables on bank profit efficiency as follows:

$$Eff_{i,t} = a_0 + a_1 \sum_{j=1}^{n} (Risk)_{i,t} + b_j \sum_{j=1}^{n} (Control)_{i,t} + e_{i,t}, \qquad (21)$$

where $Eff_{i,t}$ is the alternative profit efficiency of a bank i at a time t; $Risk_{it}$ is a vector of bank risk variables; $Control_{it}$ is a vector of bank-specific and country-level control variables; $e_{i,t}$ is the error term.

Our regressions reveal that higher risk exerts a negative impact on profit efficiency for all three country-groups considered in our sample. According to the *'bad management hypothesis'* (Berger and Mester, 1997) banks with higher risk (lower values of z-score) would divert additional resources from day-to-day activities to screening and monitoring operations that in turn would increase bank operational costs and consequently reduce bank profit efficiency. Those results complement Tsionas (2015) who has emphasized the importance of risk for bank performance.

[INSERT TABLE 6 ABOUT HERE]

Regarding the impact of liquidity risk, as measured by the liquidity ratio, results show that it has a negative impact on bank profit efficiency. Turning to the impact of capital ratio, results report a negative effect of equity over total assets on efficiency at the 1% significance level across all three groups of countries. This finding is line with the *'agency cost hypothesis'* (Jensen and Meckling, 1979), as a decrease in leverage, for example through an increase of equity over total assets, would raise agency costs. According to this hypothesis bank managers would have the incentive to increase the risk-taking activities due to the absence of the liquidation threat that exists when a bank increases its debt and thereby decreases its capital. The final outcome would be a decline in bank profit efficiency.

Regarding the remaining bank-specific control variables, we find that the non-interest income is negatively associated to efficiency across all groups, but it is significant only for the advanced economies. The reason could be that banks with high non-interest income in advanced economies perform worse than banks with low non-interest income. This is so because non-interest income is more volatile than interest income, which in turn would reduce efficiency. On the other hand, in emerging and developing economies as banks focus primarily on interest income operations the impact of non-interest income is insignificant. Note that the ratio of securities over total assets has a statistically significant and negative impact on efficiency for all banks in the sample. With respect to the country-level control variables, we find that GDP per capita exerts a negative and significant impact on efficiency of banks in all country-groups. This suggests that increases of GDP per capita could raise banking costs stemming from higher operating expenses to supply a certain level of services. On the other hand, there is a positive correlation between efficiency and inflation, suggesting that banks across the world benefit from managing inflation expectations, and gain in terms of performance. Results further show a negative relationship between population density and efficiency, but it is significant only for developing economies. This result insinuates that in developing countries where there is a higher population density it is rather expensive to perform banking operations. Market size has a negative and significant effect for all banks in the sample. Therefore, an increase in the value of total shares traded on the stock market exchange would negatively affect efficiency. Lastly, the trend variable suggests that in developing economies bank efficiency steadily increases over time.

6. Conclusion

In this paper, we employ a novel model to measure bank alternative profit efficiency whilst we derive adjustment costs in capital, labor and funds associated to changes in efficiency. Moreover, the proposed model has certain complexities that we overcome by employing a non-parametric Local Linear Maximum Likelihood (LLML).

In the empirical section, we opt for a global banking sample and report robust bank profit efficiency scores across a plethora of countries across the world. It appears that prior to the financial crisis advanced economies exhibit the highest bank alternative profit efficiency scores. However, since the crisis emerging economies are strongly picking up the pace in terms of improving their efficiency scores. Low adjustment costs in labour seem to explain this strong catching up in efficiency of emerging economies. Regression analysis shows that risk exerts a negative impact on profit efficiency for all three country-groups considered in our sample, according to the *'bad management hypothesis'*. Equity over total assets negatively affects efficiency as the *'agency cost hypothesis'* predicts. Also, GDP per capita exerts a negative and significant impact on efficiency of banks in all country-groups.

In terms of policy implications, our results reveal that improvements in bank alternative profit efficiency are not coming free of adjustment costs. To this end, adjustment costs should be taken into account in policy making, in particular in the aftermath of the financial crisis. Our results show that the banking industry in advanced economies would benefit from labor reforms that would bring down adjustment costs and thereby increase profit efficiency. Lower labor adjustment costs in emerging economies help to explain their strong performance during the post-financial crisis period. Persistence in funds adjustment costs poses further impediments to improvements in bank profit efficiency in the period 2011 to 2013.

References

Athanasoglou, P., Brissimis, S., & Delis, M. (2008). Bank-specific, industry-specific and macroeconomic determinants of bank profitability. Journal of international financial Markets, Institutions and Money, 18(2), 121-136.

Barth, J.R., Caprio, G., Levine, R., (2004). Bank regulation and supervision: What works best? Journal of Financial Intermediation 13, 205-248.

Backé, P., and Wójcik, C. (2008). Credit booms, monetary integration and the new neoclassical synthesis. Journal of Banking and Finance, 32(3), 458-470.

Berger, A., and Mester, L. (1997). Inside the Black Box: What Explains Differences in the Efficiencies of Financial Institutions? Journal of Banking and Finance, 21, 895–947.

Berger, A., and Mester, L., (2003). Explaining the dramatic changes in performance of US banks: technological change, deregulation, and dynamic changes in competition, Journal of Financial Intermediation 12, 57–95.

Gaganis C., Pasiouras F., (2013). Financial supervision regimes and bank efficiency: International evidence, Journal of Banking and Finance, 37, 5463-5475.

Galán, J.E., Veiga, H. and M.P. Wiper, (2015). Dynamic Effects in Inefficiency: Evidence from the Colombian Banking Sector. European Journal of Operational Research, 240(2): 562-571.

Gonzalo, P. and O. Linton, (2000). Local nonlinear least squares estimation: Using parametric information nonparametrically. The Journal of Econometrics, 99, 63-106.

Henderson, Daniel J., and Parmeter, Christopher F., (2009). Imposing economic constraints on nonparametric regression: Survey, implementation and extensions. In Q. Li & J. S. Racine (Eds.). Advances in econometrics: Nonparametric methods (Vol. 25, pp. 433–469). Elsevier Science.

Hume, M., and Sentance, A., (2009). The global credit boom: Challenges for macroeconomics and policy. Journal of International Money and Finance, 28(8), 1426-1461.

IMF, (2015). World Economic Outlook, April, Washington.

Jensen, M. C., and Meckling, W. H., (1979). Theory of the firm: Managerial behavior, agency costs, and ownership structure (pp. 163-231). Springer Netherlands.

Koutsomanoli-Filippaki, A. and Mamatzakis, E., (2009). Performance and Merton-type Default Risk of Listed Banks in the EU: a Panel VAR Approach, Journal of Banking and Finance, 33, 2050–2061.

Koutsomanoli-Filippaki, Anastasia I. and Mamatzakis, Emmanuel C., (2011). Efficiency under quantile regression: What is the relationship with risk in the EU banking industry?, Review of Financial Economics, Elsevier, vol. 20(2), pages 84-95, May.

Kumbhakar, S.C., (1997). Modeling Allocative Inefficiency in a Translog Cost Function and Cost Share Equations: An Exact Relationship. Journal of Econometrics 76, 351-356.

Kumbhakar, S.C., Lovell, C.A.K., (2000). Stochastic Frontier Analysis. Cambridge University Press, New York.

Kumbhakar, S.C. and Tsionas, E.G., (2005). Measuring Technical and Allocative Inefficiency in the Translog Cost System: A Bayesian Approach. Journal of Econometrics 126, 355-384.

Kumbhakar, S. C., Park, B. U., S. Leopold and Tsionas, E. G., (2007). Nonparametric stochastic frontiers: A local maximum likelihood approach. Journal of Econometrics, Elsevier, vol. 137(1), pages 1-27, March.

Kumbhakar, S. C., and Tsionas, E.G., (2010). Estimation of production risk and risk preference function: a nonparametric approach. Annals of Operations Research, 176, 369–378.

Lozano-Vivas A., Pasiouras F., (2010). The impact of non-traditional activities on the estimation of bank efficiency: International evidence, Journal of Banking and Finance, 34, 1436-1449.

Mamatzakis E., Tsionas M.G., Kumbhakar S.C., Koutsomanoli-Filippaki A., (2015), Does labour regulation affect technical and allocative efficiency? Evidence from the banking industry? Journal of Banking and Finance, 61 (Supplement 1), S84-S98.

Tran, K. C. and M. G. Tsionas, (2016). Zero-inefficiency stochastic frontier models with varying mixing proportion: A semiparametric approachOriginal Research Article European Journal of Operational Research, Volume 249, Issue 3, 16 March, Pages 1113-1123.

Tsionas, E. (2006). Inference in dynamic stochastic frontier models. Journal of Applied Econometrics, 21, 669–676.

Tsionas, E., (2015). Parameters measuring bank risk and their estimation. European Journal of Operational Research, 31, 1-14.

Tsionas, E., 2016. Notes on technical efficiency estimation with multiple inputs and outputs. European Journal of Operational Research, Volume 249, Issue 2, 1 March, Pages 784-788.

Tzeremes N. G., (2015). Efficiency dynamics in Indian banking: A conditional directional distance approach. European Journal of Operational Research, 240(3), 807-818.

World Bank, (2014). World Bank Economic Indicators, Washington.

Table 1. Descriptive statistics of main variables.

	Advanced economies				Emerging economies				Developing economies			
Variables	Mean	Sd	Min	Max	Mean	Sd	Min	Max	Mean	Sd	Min	Max
Bank outputs and input prices												
Total assets	17951329	9.93E+07	225.5	2.2E+09	9659393	7.33E+07	101.940	2.25E+09	1255046	2942407	0.0720	4.30E+07
Alt Profit	16.62951	.8904101	0	17.4859	14.4574	1.04489	0	17.59549	12.9612	3.90292	0	14.05373
Total costs	644465	3571144	1.330	1.0E+08	441730	2307282	12.3027	5.83E+07	82203	171251.4	0.0099	2814993
Net loans	9036183	4.26E+07	19.71	7.5E+08	5152601	3.80E+07	13.3233	1.15E+09	626854	1375358	0.0545	1.62E+07
Other earning assets	7354650	5.32E+07	25.15	1.7E+09	3796769	3.37E+07	14.0146	1.03E+09	449156	1335925	0.0050	2.67E+07
OBL	4536488	54.8E+07	0	2.3e+09	3332136	1.79e+07	0	2.84e+08	262626.2	1167056	0	1.88e+07
Price of fund	2.4624	5.7263	0.001	468.807	8.9291	18.01242	0.0007	351.3571	5.7072	3.889328	0.0613	34.95666
Price of physical capital	201.4653	601.8296	1.101	12528.5	415.9367	821.9096	1.5029	6467.391	140.6929	184.7081	0.2625	2445.537
Price of labor	1.1191	0.7208	0.000	15.2941	2.521	2.043134	0.0002	26.72218	2.1607	1.654687	0.0606	18.24695
Nonperforming loans	336033	2275395	0.092	7.5E+07	179375	888629.6	0.0265	3.36E+07	48030	147593.3	0.0020	2931450
Equity	1032482	5133599	19.57	1.3E+08	754589	4772551	29.6059	1.52E+08	133758	356901.8	0.0109	5917863
Interest expenses	363291	2302515	0.336	9.9E+07	260652	1447873	0.0295	3.85E+07	46658	116611.3	0.0052	2210570
Other operating expense	135577	760389	0.181	2.2E+07	94250	434416.4	3.9951	9503104	18588	40075.09	0.0018	1238709
Personnel expense	145615	827045	0.420	1.8E+07	86828	480039.3	1.6739	1.24E+07	16957	32225.98	0.0026	344906.9
Banks specific and control variables												
Z-score	0.6965	1.2223	-6.32	6.7620	0.8081	1.0480	-5.8421	6.3786	0.8443	1.1218	-5.4661	6.0934
Capital ratio	8.3162	4.6035	0.060	64.75	14.7165	10.0309	0.4700	95.5900	13.0949	9.7063	0.2100	95.4
Non Interest	0.404	0.8522	-5.66	22.7547	1.1228	1.5497	-5.3251	21.0782	1.2440	1.5983	-1.2858	32.4401
Liquidity ratio	15.1238	13.1133	-5.25	94.489	26.3849	16.1373	0.0000	94.8838	23.4960	13.2778	-3.1273	83.6178
Securities	30.0283	34.6153	0.000	1800.394	40.3673	178.8515	0.0000	13994.42	32.3383	33.2318	0.0000	1095.566
GDP per capita	10.5394	0.2823	8.517	11.1244	8.3914	0.8853	6.3319	11.0166	7.6975	1.0901	5.7024	11.3168
Inflation	1.2208	2.0805	-5.39	20.2955	10.4568	7.8728	-27.6317	102.3255	7.6531	5.9833	-3.7058	80.75
Population density	242.0769	685.3777	2.527	7589.143	93.6112	172.6893	2.4936	1733.9830	226.5159	302.7319	3.1467	1312.72
Market size	28.5054	2.1779	16.71	31.7901	25.5037	2.6935	13.7561	29.8234	19.4081	2.3754	10.2742	24.9666

Notes: The Table reports the average values of variables used for estimation in each group of economies. Total assets; Alt profit is the alternative profit; total costs = total interest expenses + overheads; net loans = gross loans – nonperforming loans; other earning assets; off balance sheet items is OBL; nonperforming loans; equity are reported in thousand USD. Price of fund = total interest expenses/total customer deposits; price of physical capital = other operating expenses/fixed assets; price of labour = personnel expenses/total assets. Z-score= (1+ROE)/ (Standard Deviation of ROE); Size= natural logarithm of total assets; Capital ratio = equity over total assets; Liquidity ratio= liquid assets over total assets; Non interest = net fees, commission and trading income over total assets; Securities/TA= total securities over total asset. As country variables we employ: GDP per capita; Inflation; Population density is the number of people per square kilometer; Market size= value of total shares traded on the stock market exchange.

Table 2: Alternative bank profit efficiency in advanced economies.

Country	Efficiency	Country	Efficiency
Australia	0.92	Japan	0.85
Austria	0.84	Latvia	0.82
Belgium	0.94	Malta	0.73
Canada	0.85	Netherlands	0.81
Cyprus	0.78	New Zealand	0.85
Czech Republic	0.84	Norway	0.83
Denmark	0.89	Portugal	0.71
Finland	0.82	Singapore	0.87
France	0.85	Slovakia	0.80
Germany	0.91	Slovenia	0.81
Greece	0.71	Spain	0.76
Hong Kong	0.83	Sweden	0.83
Ireland	0.75	Switzerland	0.85
Israel	0.86	Taiwan	0.83
Italy	0.83	United Kingdom	0.93
		USA	0.93

Note: Classification of countries is based on IMF World Economic Outlook. The Table reports efficiency scores for each country in our sample. Authors' estimations.

Table 3: Alternative bank profit efficiency in emerging economies.

Country	Efficiency	Country	Efficiency
Albania	0.72	Malaysia	0.84
Angola	0.75	Namibia	0.55
Argentina	0.71	Nigeria	0.78
Azerbaijan	0.77	Oman	0.82
Bahrain	0.79	Pakistan	0.73
Bolivia	0.77	Peru	0.75
Bosnia & Herz.	0.76	Philippines	0.91
Brazil	0.77	Poland	0.83
Bulgaria	0.71	Qatar	0.85
Chile	0.77	Romania	0.79
China	0.79	Russia	0.71
Colombia	0.73	Saudi Arabia	0.79
Hungary	0.80	South Africa	0.90
India	0.83	Thailand	0.88
Indonesia	0.81	Trinidad & Tobago	0.74
Kazakhstan	0.83	Turkey	0.80
Kuwait	0.79	UAE	0.87
		Venezuela	0.79

Note: Classification of countries is based on IMF World Economic Outlook. The Table reports efficiency scores for each country in our sample. UAE stands for United Arab Emirates. Authors' estimations.

Table 4: Alternative bank profit efficiency in developing economies.

Country	Efficiency	Country	Efficiency
Andorra	0.88	Jordan	0.91
Armenia	0.78	Kenya	0.60
Bahamas	0.82	Lebanon	0.84
Bangladesh	0.77	Lithuania	0.78
Belarus	0.81	Mauritius	0.77
Benin	0.78	Moldova	0.73
Bermuda	0.73	Mozambique	0.65
Botswana	0.51	Nepal	0.60
Cambodia	0.55	Panama	0.77
Costa Rica	0.59	Senegal	0.65
Croatia	0.87	Serbia	0.60
Dominican Rep.	0.76	Sri Lanka	0.78
Ecuador	0.75	Swaziland	0.73
Egypt	0.79	Tanzania	0.69
El Salvador	0.81	Uganda	0.63
Ethiopia	0.55	Ukraine	0.77
Georgia	0.75	Uruguay	0.78
Ghana	0.63	Vietnam	0.68
Honduras	0.69	Zambia	0.61
Jamaica	0.72		

Note: Classification of countries is based on IMF World Economic Outlook. The Table reports efficiency scores for each country in our sample. Authors' estimations.

Table 5: The adjustment cost in alternative profit efficiency due to K, L, F (capital, labour and funds respectively).

	Advanced			Emerging			Developing		
Year	**K**	**L**	**F**	**K**	**L**	**F**	**K**	**L**	**F**
2001	-0.071	-0.092	-0.317	-0.117	-0.225	-0.223	-0.22	-0.222	-0.301
2002	-0.083	-0.134	-0.319	-0.119	-0.224	-0.22	-0.221	-0.225	-0.303
2003	-0.091	-0.144	-0.322	-0.12	-0.225	-0.254	-0.232	-0.281	-0.303
2004	-0.101	-0.143	-0.335	-0.131	-0.221	-0.261	-0.255	-0.313	-0.305
2005	-0.102	-0.143	-0.334	-0.144	-0.312	-0.272	-0.261	-0.315	-0.371
2006	-0.115	-0.144	-0.335	-0.171	-0.322	-0.334	-0.282	-0.323	-0.451
2007	-0.225	-0.327	-0.671	-0.344	-0.333	-0.617	-0.291	-0.471	-0.503
2008	-0.233	-0.412	-0.682	-0.358	-0.356	-0.717	-0.414	-0.512	-0.544
2009	-0.244	-0.433	-0.505	-0.41	-0.313	-0.671	-0.562	-0.561	-0.582
2010	-0.25	-0.402	-0.561	-0.414	-0.276	-0.633	-0.567	-0.477	-0.653
2011	-0.221	-0.387	-0.482	-0.366	-0.251	-0.652	-0.451	-0.428	-0.703
2012	-0.205	-0.351	-0.471	-0.301	-0.23	-0.628	-0.178	-0.17	-0.881
2013	-0.114	-0.261	-0.31	-0.316	-0.187	-0.551	-0.134	-0.128	-0.872
2000-07	-0.113	-0.161	-0.376	-0.164	-0.266	-0.312	-0.252	-0.307	-0.362
2008-10	-0.242	-0.416	-0.583	-0.394	-0.315	-0.674	-0.514	-0.517	-0.593
2011-13	-0.180	-0.333	-0.421	-0.328	-0.223	-0.610	-0.254	-0.242	-0.819
2000-13	-0.158	-0.261	-0.434	-0.255	-0.259	-0.464	-0.313	-0.340	-0.521

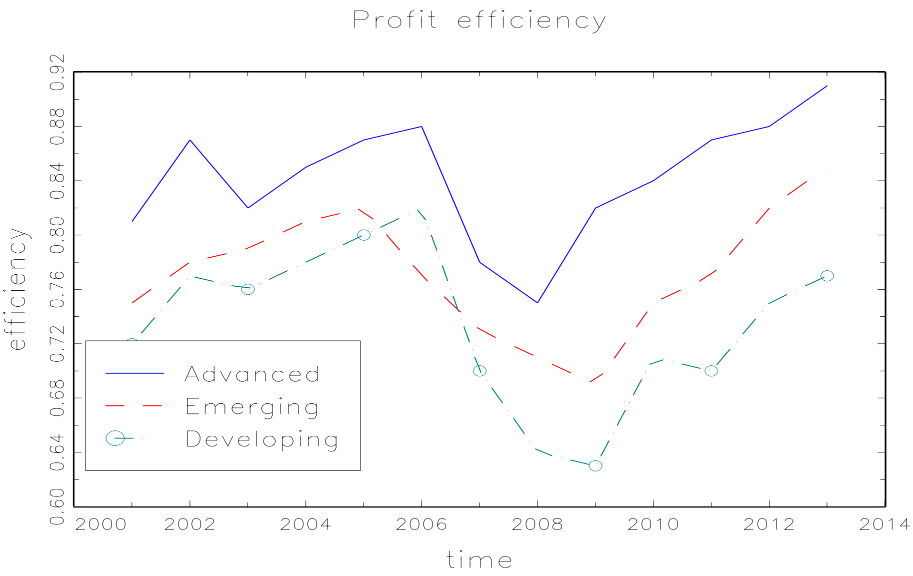
Notes: The Table reports the elasticity of alternative profit efficiency with respect to variable inputs capital, labor and funds (K, L, F respectively). Authors' estimations.

Table 6: Effect of control variables on alternative profit efficiency.

	Advanced	Emerging	Developing
Z-score	-0.033**	-0.065**	-0.027**
	(0.012)	(0.013)	(0.014)
Capital ratio	-0.035**	-0.014**	-0.012**
	(0.0031)	(0.0010)	(0.0014)
Non interest	-0.0021**	-0.0032	-0.0065
	(0.00014)	(0.0122)	(0.0242)
Liquidity ratio	-0.0021**	-0.0035**	-0.0011**
	(0.00022)	(0.00019)	(0.00015)
Securities	-0.0015**	-0.0133**	-0.477**
	(0.00013)	(0.0051)	(0.0117)
GDP per capita	-0.0032**	-0.0065	-0.0014
	(0.0011)	(0.0144)	(0.0015)
Inflation	0.0012	0.0032	0.0055**
	(0.0015)	(0.0022)	(0.0012)
Population density	-0.0014	-0.0032	-0.0071**
	(0.0025)	(0.0032)	(0.0021)
Market size	-0.0013	-0.0044**	-0.0065**
	(0.0012)	(0.0014)	(0.0018)
Trend	0.0013	-0.0012	0.0011**
	(0.0022)	(0.0013)	(0.0004)
R_2	0.914	0.896	0.954

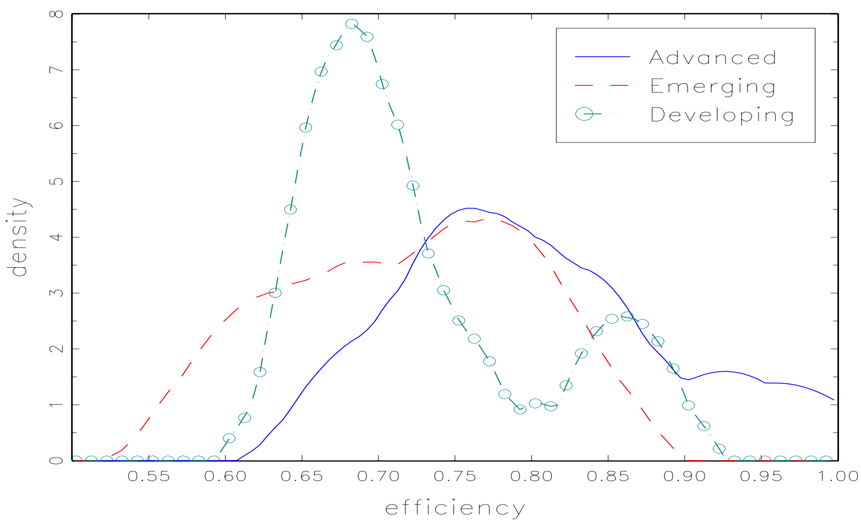
Notes: Authors' calculations. The table provides the average elasticities of technical efficiency with respect to the control variables. To provide a measure of fit we correlate alternative profit efficiency u_{it} with its predictor, say $\hat{u}_{it}$, computed directly using the equations in the table above.

Figure 1: Alternative profit bank efficiency over time.



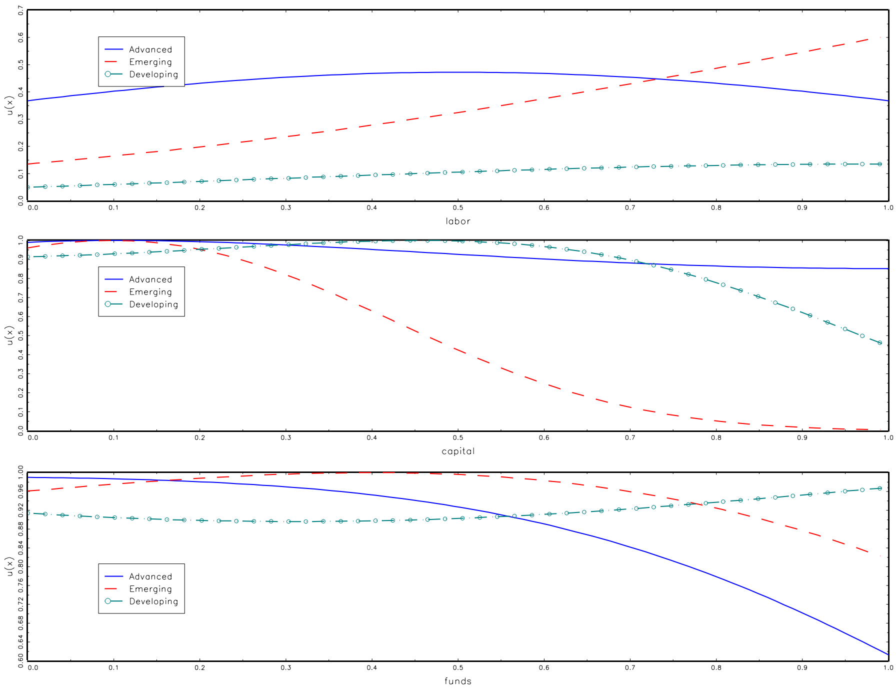
Notes: The Figure shows efficiency every year for each group of economies. Authors' estimations.

Figure 2: Density of global alternative profit bank efficiency.



Notes: The Figure shows density of bank efficiency. Authors' estimations.

Figure 3: Adjustment costs for capital, labour and funds (K, L, and F).



Notes: Authors' estimations. Units of measurement are adjusted so that the lowest value is zero and the maximum value is one.