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The nexus between bank efficiency and leverage

Konstantinos N. Baltas

Finance Group, Essex Business School, University of Essex, Colchester, UK

Correspondence
Konstantinos N. Baltas, Finance Group, Essex Business School, University of Essex, Wivenhoe Park, Colchester, CO4 3SQ, UK.
Email: k.baltas@essex.ac.uk

Abstract

In this paper, we shed light on the impact of leverage on efficiency by introducing a new banking efficiency indicator that includes efficiency and stability conditions. This indicator relies on the leverage as a proxy of a bank's risk and stability. Banks' leverage played an important role in the last financial crash as well as in the Basel III regulatory rules. The results of the econometric investigation using a large sample of American commercial banks show that profit efficiency indicators including leverage are better predictors of future profits than current indicators, including other measures of bank risk. This is particularly evident for the period during the 2007–2009 financial crisis. Our findings have important policy implications, particularly in light of the recently implemented optimal leverage ratio.

KEYWORDS

bank efficiency, business cycles, financial stability, leverage, stochastic profit frontier, US banking sector

1 | INTRODUCTION

The latest financial crisis revealed an interesting phenomenon where even highly efficient banks failed despite adhering to the Basel II rules. This has raised doubts about the effectiveness of these regulations and the efficiency models of banking. Researchers Demirguc and Huizinga (2010) investigated the causes of the financial crisis and found that between 1995 and 2007, banks engaged in non-lending and non-deposit activities using leverage, leading to increased risk and returns from fee income. Similarly, Beltratti and Stulz (2012) discovered that poorly performing banks during the crisis had extremely high returns and leverage in 2006, while better-performing banks had lower returns and leverage. In line with this, Berger and Bouwman (2013) demonstrated that having capital always increases the likelihood of small banks' survival and enhances the performance of medium and large banks, especially during banking crises.

The reason for these findings is that banks act rationally to pursue profits during economic booms, while accepting losses during downturns, as the profit potential during booms is too enticing to ignore. Leverage is used to increase risk-taking and capitalize on investment opportunities in the present. However, in times of economic hardship, highly leveraged banks may be compelled to sell off their holdings at prices that are lower than their true worth. Therefore, the use of leverage intensifies the variability of investment and profits and the balancing act between effectiveness and steadiness.

Surprisingly, up to the present banking efficiency models do not address the impact of leverage on banking stability and long-term risk. Even early indicators of profit or cost efficiency do not factor in risk. Instead, they assess how close a bank is to achieving maximum profit or minimum cost based on input and output prices and other variables. As a result, studies on banking efficiency (such as Hughes et al., 1996 and Hughes et al., 2000) incorporate risk measures into efficiency indicators and use a best-practice risk-return stochastic frontier to determine the highest expected return for a given level of risk. Inefficiency is measured by the difference between a bank's potential return and its noise-adjusted expected return, relative to its peers with similar levels of risk. However, the latest efficiency indicators are still focused on the short-term and do not take into account a bank's ability to perform over the long run. However, the latest measures of efficiency focus only on the short term and do not consider whether a bank can withstand adverse conditions over the long run. As a result, a bank that takes on less risk but has better stability conditions may be considered less efficient than a similar bank on the efficient frontier that takes on more risk. Additionally, current efficiency tests assume that any combination of risk and return is equally efficient as long as it is on the efficiency frontier. However, bank managers often have to balance the desire for current profits against the need to ensure future opportunities. This trade-off arises because banks that take on too much risk relative to their resources are more likely to become insolvent when faced with adverse economic conditions. While increased risk-taking may lead to valuable investment opportunities, decreased risk-taking can protect a bank from financial distress, such as liquidity crises, regulatory intervention and forfeiture of its charter. Empirical evidence suggests that this trade-off is relevant, as more leveraged and profitable banks before a crisis may be more vulnerable to adverse economic conditions. However, the failure of current efficiency models to consider this important trade-off between efficiency and stability (as noted by Haldane et al., 2001) may reduce the predictive power of any efficiency model of banking and lead to incorrect conclusions about a bank's efficiency.

Thus, our study contributes to the strand of banking efficiency literature by presenting a new indicator of profit efficiency which takes into account the trade-off that bank managers face between efficiency and stability. Specifically, it considers both the propensity to risk (ex-ante measure of risk) reflected by the vulnerability of the bank to changes to the financial market conditions and the realized risk (ex-post measure of risk), due to mismanagement of the bank. Moreover, for the first time in the literature, we empirically test the deviation of the ordering of the banks according to their banking efficiency estimates, deriving from the conventional in the literature indexes and the new profit efficiency and stability adjusted index, in three different states of the economy, that is, before, during and in the aftermath of the last financial crisis. Finally, yet importantly, we compare the explanatory and predictive power of all profit efficiency indicators with regard to the growth of profits around the crisis period.

This leads us to the next contribution of our paper which is related to the strand of research on the optimal leverage ratio. The theoretical literature examining the impact of introducing a non-risk-based leverage ratio in conjunction with a risk-based capital framework produces mixed results on whether it reduces risk-taking (Barth & Seckinger, 2018; Blum, 2008; Hugonnier & Morellec, 2017; Kiema & Jokivuolle, 2014). In this paper, we contribute to this debate by shedding light on the impact of leverage on efficiency. Our proposed efficiency measure considers leverage as an indicator of a bank's stability, following the approach of Haldane et al. (2010). Essentially, we assume that a bank's level of efficiency is higher if it exhibits the same risk and returns but with lower leverage than its counterpart. A low-leveraged bank has the potential to benefit more from future profits during a boom, and can more readily mitigate losses in the face of adverse economic conditions. By incorporating leverage into the efficiency frontier, we can gain a more comprehensive understanding of a bank's overall soundness, as it enables us to evaluate whether the bank's current profit expansion comes at the expense of future profits or losses. Leverage not only estimates the impact of external negative effects on a bank's balance sheet, but also accounts for the likely impact of a bank's failure on the wider economic system, rendering some banks too leveraged to fail. We contend that if this new efficiency measure incorporating leverage proves to be a superior predictor of a bank's soundness in a more dynamic context, it should also be a more precise predictor of future profits than existing risk-adjusted efficiency measures, both during booms and busts. The last financial crisis provides a natural experiment for testing this hypothesis and determining the optimal leverage for surviving banks.

With this in mind, using a sample of US commercial banks over the period 2003–2012, we estimate whether those that were more efficient and stable before the financial crisis were better able to withstand its impact. Our findings demonstrate strong empirical evidence that emphasizes the importance of leverage and its essential inclusion in the estimation of profit efficiency. The superiority of our proposed profit efficiency index, that accounts for both a bank's risk and stability conditions, with respect to both its explanatory and predictive power, is supported in all empirical specifications compared to those currently used in the literature. We also show that our risk and stability adjusted index is more stable than conventional indexes, as it has the least deviation in the ranking of the banks according to their profit efficiency scores in all three period of the crisis, that is, pre-crisis, during-crisis, post-crisis. The results remain consistent after a series of robustness tests that we conducted and present in this paper.

This study makes important inferences for policy implications in light of the current Basel III regulatory framework and particularly the implementation of the non-risk-based leverage ratio. Given the mixed evidence in the literature of the leverage ratio's effect on risk-taking, our findings could lead to the creation of another avenue in determining the optimal leverage ratio via the profit efficiency channel. Moreover, as it is noted by Gaganis et al. (2021), recent research has emphasized the significance of bank efficiency in promoting economic growth (Berger et al., 2004; Hasan et al., 2009) and recommended that it should be considered in the broader economic context. Therefore, by using our suggested efficiency indicator, policymakers can closely monitor the joint optimal level of efficiency and stability, which could help to reduce the cost of regulatory interventions and facilitate financial institutions' adaptation to uncertain and unfavourable market conditions. This would contribute to a more effective adjustment process and make them better prepared to withstand potential adverse economic situations.

The remainder of the paper is organized as follows. Section 2 introduces the key contributions to the literature on banking efficiency and risk on which we base our subsequent analysis. Section 3 discusses the theoretical framework and presents our proposed efficiency indicator. Section 4 explains the empirical methodology as well as the models that we estimate. Section 5 deals with the features of the dataset and Section 6 reports and discusses the econometric results. The final section provides some concluding remarks.

2 | BANKING EFFICIENCY AND RISK

Many studies fall into the category of "non-structural and structural approaches" that examine bank efficiency. The non-structural approach involves comparing productivity and performance ratios across banks and examining their relationship with investment strategies and various bank characteristics such as governance quality, product mix, and so on. On the other hand, the structural approach typically employs cost minimization or profit maximization economics, with the performance equation representing a cost or profit function. In more recent times, the optimization problem is formulated as the maximization of managerial utility, where the manager balances risk and expected return. In terms of the structural performance equation, it can be applied to the data as a standard relationship that assumes all banks have the same level of efficiency in minimizing costs or maximizing profits, taking into account a random error o_i, that is assumed to follow a normal distribution. On the other hand, the structural performance equation can be estimated as a stochastic frontier to capture best-practice and to gauge inefficiency. This involves quantifying the gap between the optimal level of performance and the actual level achieved. On the stochastic frontier, the error term, o_i, consists of two components: a two-sided random error that represents noise ($v_{\pi i}$) and a one-sided error representing inefficiency ($u_{\pi i}$).

The standard profit function studied in the literature (Berger & Mester, 1997), in log form, is:

$$\ln(v_i) = \ln g(p_i, u_i, z_i, k_i) + v_{\pi i} - u_{\pi i}, \tag{1}$$

where v denotes profits; p is the vector of prices of the variable outputs; u is the vector of prices of variable inputs, z is a vector of variables that capture key components of the itk bank's technology (e.g., inputs or outputs, such as physical plant, which cannot be altered quickly), k refers to a group of market or environmental variables that could influence performance. (e.g., market conditions, regulatory restrictions) but are not a choice for firm management, $v_{\pi i}$, represents random error; and $u_{\pi i}$ represents inefficiency that reduces profits.

Profit efficiency refers to the proportion of maximum profits a bank can earn given its resources, net of random error, or the ratio of the actual profits to the maximum profits that could be attained if the bank operated as efficiently as the best-practice bank in the sample.

The standard profit function assumes that markets for inputs and outputs are completely competitive. However, if banks hold market power, an alternative profit function (Berger & Mester, 1997) is used where they consider the output quantity and input price (p) as given, and they try to maximize profits by changing the input quantity and output price (u).

Neither the traditional nor the alternative profit functions or frontiers are calculated with regard to banks' capital structure or their risk preferences. Yet, as pointed out by Hughes et al. (1999, 2000), this is a serious omission, due to the fact that a bank's production methods incorporate their capacity to spread and offset various types of risk, and because the decisions made by bank managers may reflect their motives to both assume and diversify risks. Therefore, efficiency models that followed (Hughes et al., 1996, 1999, 2000; Hughes et al., 2001) take into account a broader objective function than just maximizing profits. These models contain measures of risk associated with production plans and establish an estimation of the most efficient risk-return frontier, against which inefficiency can be evaluated. Specifically, they propose a stochastic frontier estimation, like Equation (1), which delivers the highest anticipated return for a specific risk exposure:

$$E(v_i/h_i) = \beta_0 + \beta_i\sigma_i + \beta_2\sigma^2 + {}_iv_{\pi i} - u_{\pi i} \quad (2)$$

where h_i denotes equity and $E(v_i/h_i)$ expected return on equity; σ_i is the standard error of profit, a measure of risk.

The inefficiency of a bank's return is the difference between its potential return and its noise-adjusted expected return, measured against other banks that operate with the same level of return risk.[1]

The efficiency models proposed by Hughes et al. (2000) for a sample of American commercial banks demonstrate that outcomes from the utility maximization model, which factors in risk, differ significantly from the standard profit-maximization model that disregards risk. Similar findings are discovered by Koetter (2008) for German universal banks. Furthermore, Koetter discovers proof that low profitability efficiency might stem from alternative, yet efficiently chosen risk-return trade-offs.

Another important strand of the literature investigates the relationship between efficiency and risk and identifies the most appropriate measure of risk. There are *ex-ante* and *ex-post* measures of risk, with the latter including non-performing loans to total loans, loan-loss provisions to total loans, and the risk-weighted assets to total assets ratio (Casu et al., 2006). Berger and Humphrey (1997) argue that problem loans should be included as explanatory variables of efficiency only if they arise from "bad luck" external to the bank, and not if they are caused by poor management practices within the bank. However, bad loans only account for a fraction of the business (i.e., loans). A broader risk measure used in the literature is the variance of profits, assessed *ex-ante* or *ex-post*. However, an ex-post risk measure utilizes information from a fixed number of periods in the past, assuming that risk is exogenous to other bank characteristics. Many scholars, including Kim and Santomero (1988), Rajan (2005), Diamond and Rajan (2000), Hughes (1999), Hughes et al. (2001), DeYoung et al. (2001), Freixas and Rochet (2008), Degryse et al. (2009), and Delis et al. (2014), acknowledge that banks make risk decisions concurrently with their expected profits and other banks' characteristics, mainly capital and liquidity. Delis et al. (2014) propose a model where profits, risk (the variance of profits), and other bank characteristics (such as capital and liquidity) are simultaneously determined. They reveal that unlike other risk indicators that remain constant throughout the period, the endogenous risk indicator of US banks is stable up to 2001 and accelerates rapidly thereafter, up to 2007. Along the same lines, Chen (2012) suggests that risk can be considered an undesirable output or an endogenous variable that should be directly incorporated into the production or cost function. He clarifies that risk is an *ex-ante* concept, while undesirable output is an ex-post concept. Using the reciprocal capital adequacy ratio as the risk input factor, Chen (2012) demonstrates that neglecting the risk input could lead to a distortion of total factor productivity estimation for banks, including a biased estimation of the technological frontier and an overestimation of the degree of economies of scale. Altunbas et al. (2000) obtained similar results for Japanese banks, revealing that optimal bank size is much smaller when risk and quality factors are taken into account. However, these factors do not seem to impact X-inefficiency. Nonetheless, Altunbas et al. (2000) find that scale inefficiencies dominate X-inefficiencies.

The findings indicate that the introduction of risk as a factor in measuring efficiency affects the conclusions regarding the efficiency of banks. However, there are conflicting results in the empirical evidence on the relationship between efficiency and risk. While Hughes and Moon (1997) and Hughes and Mester (1998) discover that inefficient American banks tend to be riskier, Altunbas et al. (2007) find that inefficient European banks tend to hold more capital and take on less risk. Fiordelisi et al. (2011) do not find a significant relationship between capital and risk for European banks, using both *ex-post* and forward-looking measures of risk. They also find that profit efficiency negatively Granger-causes risk in European banks. These results suggest that American and European banks may respond to different incentives, such as the regulatory hypothesis or moral hazard hypothesis, or differ in the quality of their management. The authors highlight the importance of achieving long-term efficiency gains to support financial stability goals.

The last remark addresses the issue of whether current efficiency indicators are also suitable for measuring banking efficiency in the long run. This is due to the notion that theoretically, we would expect that efficient banks would fulfil two conditions: to produce the amount of output which maximizes profits or minimizes costs (economic efficiency) and to mix output and inputs to obtain the maximum profit or minimum cost at the lowest possible risk; in other words, to combine the portfolio in such a way as to reach a point on the efficiency frontier. However, higher productivity today may be achieved by undertaking excessive risks, and this may weaken the stability of the bank. With this in mind, we argue that current measures of efficiency do not take into account this important trade-off, as they do not consider the capability of the bank to face adverse conditions in the long run. Indeed, in a very recent study, Assaf et al. (2019) provide evidence that profit efficiency may reflect temporary high returns from risky investments during normal times, which are reversed during financial crises. The implication is that current profit efficiency indicators are not a reliable measure of bank quality.

In other words, an efficient indicator aiming to detect best practices in bank management, should take into account not only the probability that inputs and outputs are not optimally combined but also how the choice of those specific levels of inputs and outputs may affect a bank's stability as well. Accounting for financial stability issues implies evaluating risk and efficiency in the long run; this requires the inclusion of forward-looking risk indicators in the measurement of efficiency. However, neither variance of expected profits nor other forward-looking risk indicators used in the literature (expected default, loan loss provision), take into account the trade-off that may exist between a bank's current profits and future profits, due to the business cycle that characterizes market economies.

3 | HYPOTHESIS DEVELOPMENT—LEVERAGE

As previously mentioned, prior to the financial crisis, banks expanded their balance sheets through non-lending and non-deposit activities, fuelled very often by leverage. While leverage can boost profits during economic booms, it also leads to greater losses during downturns, as banks may be forced to sell assets below their fundamental values to meet short-term borrowing obligations. This is because if banks use short-term borrowing to support long-term investments, they may be unable to sustain those investments during economic downturns. During these periods, banks may want to hold onto these undervalued investments, but creditors may demand their liquidation. Research by Shleifer and Vishny (2010) demonstrated that leveraged banks not only pose a risk to their own stability but also contribute to systemic risk through their profit-seeking behaviour. The literature on the financial crisis has identified high levels of leverage among financial institutions worldwide as a major contributor to the build-up of structural weaknesses and adverse market dynamics in the lead-up to the crisis. Therefore, in response to concerns about bank stability after the crisis, the Basel III framework was introduced. This framework includes a leverage ratio requirement in addition to minimum capital requirements based on internal ratings and new liquidity requirements established under Basel II.

There is a difference between leverage and other indicators of risk. Non-performing loans are an indicator of risk that are revealed only after the crisis hits and loans cannot be repaid, and the variance of expected profits is a short-run forwardlooking indicator of risk. By contrast, leverage is an indicator of risk in the long run, since it considers the trade-off that may exist between current and future profits, due to the fact that banks, as it was aforementioned, that take on excessive risk relative to their resources face a higher probability of insolvency when adverse events occur in the future. Specifically, Geanakoplos (2009), Galo and Thomas (2012), Adrian and Shin (2013) presented models of procyclicality of leverage, and Adrian and Shin (2010) and Jordà et al. (2011), among others, provided empirical evidence supporting this hypothesis. That is, leverage incorporates stability issues, which are not considered by other risk indicators, and the profit efficiency indicator that includes leverage is more closely tied to long-term bank risk than short-term risk.

To measure both efficiency and stability of the bank we consider a modified version of the standard profit efficiency measure which is determined by the following stochastic frontier model under a translog production function:

$$\begin{aligned}\ln(Prof_{it}) = {} & \beta_0 + \sum_{l=1}^{3}\beta_{ql}\ln q_{it,l} + \sum_{s=1}^{2}\beta_{ps}\ln p_{it,s} \\ & + \frac{1}{2}\sum_{l=1}^{3}\sum_{s=1}^{2}\beta_{qlqs}\ln q_{it,l}\ln q_{it,s} \\ & + \frac{1}{2}\sum_{l=1}^{2}\sum_{s=1}^{2}\beta_{plps}\ln p_{it,l}\ln p_{it,s} \\ & + \sum_{l=1}^{3}\sum_{s=1}^{3}\beta_{qlps}\ln q_{it,l}\ln p_{it,s} + \beta_{NPI}\ln NPI_{it} \\ & + \beta_{\sigma 1}\ln(\sigma 1_{it}) + \beta_{\sigma 2}\ln(\sigma 2_{it}) + \beta_t T + \frac{1}{2}\beta_{tt}T^2 \\ & + v_{it} - -u_{it}.\end{aligned} \tag{3}$$

As a dependent variable (i.e., *Prof*) we use total profits before tax (*PBT*). In order to tackle the issue of negative profits (losses) we follow the approach proposed by Bos and Koetter (2011) and used by the vast majority of the literature (e.g., Barra et al., 2022; Castro & Galán, 2019; Degl'Innocenti et al., 2018; Delis et al., 2014; Kalyvas & Mamatzakis, 2017, among others) that allows the use of all the available information in the sample. Specifically, we left-censor profit but assign a value of one to those banks with negative profit. In order to include all information available on the censored part of profit we specify an additional independent variable NPI (for Negative Profit Indicator). Consequently, we define profit to be equal to one for positive values of profits, and equal to the absolute value of profit for a loss-incurring bank.

In the estimation of profit efficiency, we make two assumptions. First, efficiency is measured by how close a bank comes to earning maximum profits given its output levels rather than its output prices. That is, banks have some market power. To define outputs and input prices we follow the intermediation approach (Delis et al., 2014; Hughes & Mester, 1998; Sealey & Lindley, 1977). Under this approach, a bank uses labour and physical capital to attract deposits, which in turn are used to fund loans and other earning assets. We specify the two mainstream types of outputs as total loans (q_1) and total other earning assets (q_2). However, as Stiroh (2004) emphasizes, in the classical intermediation business, fee income is increasingly becoming a substitute for the revenues that can be earned on narrowing interest margins. To take into consideration this development, we also account for total off-balance sheet activities (OBS), credit commitments and derivatives, as an additional output (q_3). Additionally, we specify as our three types of inputs the relevant ratios of interest expenses, salary expenses, and expenses on fixed assets. Specifically, we measure the price of input (p_1) using the ratio of interest expenses to total deposits and short-term funding, the price of input (p_2) using the ratio of staff expenses to the number of employees and the price of input (p_3) using the ratio of fee and commission expenses added to administration expenses to fixed assets. Moreover, we include a time trend (T) to capture the potential technical change that occurred during the examination period in both linear and quadratic terms.[2] Lastly, ($\sigma 1$) denotes credit risk (i.e., an ex-post risk indicator) which is captured by the ratio of each bank's non-performing Loans (NPLs) to its total loans (TLs) and ($\sigma 2$) is the risk deriving from excessive leverage (i.e., an ex-ante risk indicator) that is defined by the ratio of each bank's total assets to its overall level of equity capital (Papanikolaou & Wolff, 2014).

The total asset to total equity capital ratio shows the proportion of the bank's assets, that is, loans and investments (e.g., bonds), that has been funded by its shareholders. Banks expect that the loans they grant will yield a higher return than the interest they pay to their depositors or investors in bonds. However, if the return on loans is lower than expected, the bank's equity capital will decrease because the bank must use its equity to cover the difference between deposit and lending rates. Additionally, if a loan cannot be recovered, it will be charged off, which means the bank will lose an amount equal to the loan loss. This will decrease the bank's equity capital and thus, equity is seen as a protection against losses in case loans or other investments perform poorly. Clearly, if many borrowers default on their debt commitments, the equity capital of the bank will be at risk. Should non-performing and defaulted loans accumulate, which occurs quite often during recessions, equity capital would dry out. Therefore, the ratio of total assets to total equity maps the ex-ante riskiness of a bank's asset position into the riskiness of its equity stake.

It should be noted here that the leverage indicator used in this study, that is, the total asset to total equity capital ratio, is different from the Basel III leverage ratio which is calculated by dividing the bank³s Tier 1 capital by its total leverage ratio exposure measure, including average consolidated assets, derivatives exposures and off-balance sheet items. The leverage ratio employed here measures a bank³s capital in relation to its total assets, providing a simple and easy-to-understand indicator of the bank³s leverage and risk profile. In contrast, the various capital buffers can be complex and difficult to calculate and may not always be applicable to all banks, making it harder for investors, creditors, regulators and other stakeholders to assess a bank³s risk profile. Moreover, it is less susceptible to manipulation as banks may use various accounting methods and financial instruments to adjust their capital levels. Additionally, it provides an accurate measure of a bank³s loss-absorbing capacity, since it measures a bank³s ability to absorb losses with its own funds, while the various capital buffers may include certain financial instruments that are less loss-absorbing, such as contingent convertible bonds. Finally, yet importantly, it is a more comparable measure across different banks and jurisdictions as different banks may use different accounting methods or have different risk profiles, which can make it difficult to compare their capital buffers.

Since leverage reflects more risk for a bank in the long run than in the short run, we expect the above efficiency indicator to be a better predictor of future profits of the bank than models that include only ex-post or short run ex-ante risk measures in a bank efficiency indicator.

Hence our hypothesis would suggest that: *Inslusion of leverage (as a long run ex ante indisator of rish) in tke estimation of prof it effisiensy uould insrease tke indisator's explanatory and predistive pouer.*

With this in mind, in the next section, we present our empirical strategy in testing this hypothesis, by estimating the capability of alternative profit efficiency indicators to explain and predict future profits and the probability of default using various different methods.

4 | EMPIRICAL METHODOLOGY

Our empirical strategy lies into three steps.

4.1 | Profit efficiency scores

In the first step, we compare the robustness of our profit efficiency indicators.

We would expect that more efficient banks at the onset of the crisis, other things being equal, will be able to withstand the impact of the crisis better. So, if this is true, the relative position of the banks from an efficiency point of view should be similar after and at the onset of the crisis. Conversely, if the most efficient banks change their relative position during the crisis, it implies that current tests of efficiency have little predictive power, because they do not take into account other factors that may affect a bank's risk and returns. To pursue this analysis, we create three different Markov transition matrices[3] in terms of range, that is, deciles, quartiles and 'half-tiles'[4], and allocate each bank within each category, according to its profit efficiency score derived from four alternative risk-adjusted profit efficiency indexes. Thus, the least profit-efficient banks are classified in the lowest half-tiles, quartiles, and deciles respectively, whereas the most efficient banks in the sample are allocated at the top of each respective range. With this in mind, we investigate the scale of deviation of the aforementioned ordering of banks according to their profit efficiency score with respect to each index among different time horizons. Two of those indexes already exist, whereas the remaining two are introduced by this study for the first time in the literature. Specifically, these four alternative profit efficiency indicators account for

1. an *ex-post* indicator of risk, that is, credit risk (existing),
2. both an *ex-post* and a long run *ex-ante* indicator of risk, that is, credit risk and leverage (proposed—our preferred one[5]),
3. a short run *ex-ante* indicator of risk, that is, variance of profits (existing),
4. both a short run and a long run *ex-ante* indicator of risk, that is, variance of profits and leverage (proposed),

in three different states of the economy, that is, 'pre-crisis', that is, 2003–2006; 'during crisis' that is, 2007–2009 and 'post-crisis' that is, 2010–2012.[6]

As far as the first period is concerned, we examine the variability of the difference in the banks' profit efficiency estimates between 2003 and 2006, in order to test the robustness of each profit efficiency index in normal periods. The reasoning behind this, is to test whether the performance of the profit efficiency indicators is different when the impact of the financial turmoil is not taken into account. In the same spirit, we are interested in capturing potential changes that may have occurred during the recent financial turmoil and to investigate which index is able to account for these changes more accurately. Hence, we compare each index's profit efficiency estimates between 2006 and 2009. Similarly, in the last time period we compare the profit efficiency scores of each index with respect to the aftermath of the financial crisis, that is, between 2009 and 2012.

4.2 | Explanatory and predictive power

In the second step of our empirical strategy, we address two issues. First, we compare the explanatory power of the profit efficiency indicators proposed in this study and the existing ones in the literature. Specifically, we examine which one of the four alternative profit efficiency indexes explains better the current banks' profits in three different time periods, that is, 'pre-crisis', 'during crisis' and 'post-crisis'. Thus, the following regression equations are estimated:

$$
\begin{aligned}
\ln ROE_{it} = {} & \beta_0 + \sum_{l=1}^{3}\beta_{ql}\ln q_{it,l} + \sum_{s=1}^{2}\beta_{ps}\ln p_{it,s} \\
& + \frac{1}{2}\sum_{l=1}^{3}\sum_{s=1}^{2}\beta_{qlqs}\ln q_{it,l}\ln q_{it,s} \\
& + \frac{1}{2}\sum_{l=1}^{2}\sum_{s=1}^{2}\beta_{plps}\ln p_{it,l}\ln p_{it,s} \\
& + \sum_{l=1}^{3}\sum_{s=1}^{3}\beta_{qlps}\ln q_{it,l}\ln p_{it,s} + \beta_{NPI}\ln NPI_{it} \\
& + \beta_t T + \frac{1}{2}\beta_{tt}T^2 + \beta_{PE}PE_{it} + o_{it},
\end{aligned}
\tag{4}
$$

where, *ROE* (i.e., return on equity) is a proxy for bank profitability, *PE* denotes alternative risk adjusted profit efficient indicators that is, a. credit risk, b. credit risk and leverage, c. variance of profits, d. variance of profits and leverage.

Second, we compare the four alternative indexes in terms of their forecasting power. To be more precise, by using the three aforementioned time periods, we investigate which profit efficiency index can better capture the growth of bank profits in a 'pre-crisis', 'during-crisis' and 'post-crisis' state of the economy, respectively. In a similar manner as in the first step, we employ the same regression equation but with the basic difference that the independent variables are calculated by taking into account the past estimates of their respective coefficients:

$$\begin{aligned}\ln ROE_{it} = \beta_0 &+ \sum_{l=1}^{3} \beta_{ql,t-n} \ln q_{it,l} + \sum_{s=1}^{2} \beta_{ps,t-n} \ln p_{it,s} \\ &+ \frac{1}{2} \sum_{l=1}^{3} \sum_{s=1}^{2} \beta_{qlqs,t-n} \ln q_{it,l} \ln q_{it,s} \\ &+ \frac{1}{2} \sum_{l=1}^{2} \sum_{s=1}^{2} \beta_{plps,\,t-n} \ln p_{it,l} \ln p_{it,s} \\ &+ \sum_{l=1}^{3} \sum_{s=1}^{3} \beta_{qlps,\,t-n} \ln q_{it,l} \ln p_{it,s} \\ &+ \beta_{NPI,t-n} \ln NPI_{it} + \beta_t T + \frac{1}{2} \beta_{tt} T^2 + \beta_{PE,t-n} PE_{it} + o_{it},\end{aligned} \tag{5}$$

where n represents the forecasting horizon which is three time periods in the past in each one of the three respective states of the economy.

In this way, we investigate which index could be more adequately in line with the forthcoming distortion of the world's financial stability and the tremendous impact it had on the efficiency of various banking systems in both developed and emerging markets.

4.2.1 | Conditional specification

Next, we perform the same analysis as in the previous step, but with a fundamental difference: we differentiate our sample between banks that went bankrupt in the period 2007–2009 and those that managed to survive the first impact of the financial turmoil.

Additionally, to be able to capture any remaining adverse contagion effects, we account for the banks that became insolvent in the post-crisis years (i.e., 2010–2012) and those that sustained their viability in the aftermath of the crisis. In this way, we examine which profit efficiency measure can explain better the development of a bank's profits in both categories (i.e., 'saved' and 'failed' banks), in all three different time periods, around the last financial turmoil.

In a similar fashion as Assaf et al. (2019), we consider a bank as *insolvent* or *failed* if it was placed under receivership or closed by the Federal Deposit Insurance Corporation (FDIC), because it was unable to meet its obligations to depositors and other stakeholders and thus, included in the FDIC failure list; or experienced book-value insolvency; or technical default bank became critically undercapitalized, its equity capitalization fell below 2% of bank gross total assets (GTA) in crisis period t.

5 | DATA

Data used for the estimation of the model consists of the Call Reports of all US commercial banks during the period 2003–2012. We focus our analysis on the US banking sector because the crisis originated in the United States before spilling over to other economies around the globe. Hence, by looking at the US banking industry, we are able to better trace some of the root causes of the last financial turmoil. The key reason why we restrict our attention to commercial banks (and not, for instance, on investment or savings banks) is because the commercial banking sector is both heavily regulated and largely supervised. The data has been substantially edited to avoid inconsistencies, reporting errors and double counting of institutions. We exclude all observations for which data on any of the variables used in our study is missing. Moreover, following Berger and Mester (1997) and Delis et al. (2014), we apply an outlier rule to the variables used, corresponding to the 5th and 95th percentiles of the distributions of the respective variables.[7] This excludes extreme values that may influence the results. Our final unbalanced dataset consists of 46,553 for 7,180 US commercial banks. All data are adjusted to be in real terms, using the GDP deflator (with 2012 as the base year), obtained from the World Bank database and represented in US Dollars (Assaf et al., 2019). Table 1 presents descriptive statistics of the variables that we use in the estimation of the alternative profit function for the US commercial banking sector.

6 | EMPIRICAL FINDINGS

Before we present the results for all the three aforementioned steps of our empirical strategy, the first question we address in the paper is the impact of leverage (an indicator of a bank's risk and stability) on bank's profits.

Results reported in Table 2 show that non-performing loans and leverage have a negative impact on profits; by contrast the variance of profits is positively correlated to the latter. Thus, it seems that leverage is associated with lower best practices profits, in line with previous studies in the literature (Sunder & Myers, 1999; Titman & Wessels, 1988; Wald, 1999).

Additionally, the results in Table 2 indicate that between 2003 and 2006 the impact of the two *ex-ante* risk indicators (variance of profit and leverage) on profit efficiency of the American commercial banks decreased, while the role of the *ex-post* indicator of risk increased. By contrast, during the financial crash (from 2007 to 2009), the impact of the two *ex-ante* risk

TABLE 1 Variable definitions and summary statistics.

Panel A—Variable definitions		
Variable	**Symbol**	**Measure**
Profit before tax	PBT	Total profits before tax
Price of borrowed funds	p1	The ratio of interest expenses to total deposits and short-term funding
Price of labour	p2	The ratio of staff expenses to the number of employees
Price of physical capital	p3	The ratio of fee and commission expenses added to administration expenses to fixed assets.
Total loans	q1	Total loans
Total earning assets	q2	Total earning assets
Off-balance sheet items	q3	Off-balance sheet items
Credit risk	σ1	The ratio of each bank's non-performing loans (NPLs) to its total loans (TLs)
Leverage	σ2	The ratio of each bank's total assets to its overall level of equity capital
Variance of profits	VarProf	The variability of profits
Return on equity	ROE	The bank return on equity
Return on assets	ROA	The bank return on asset

Panel B—Summary statistics						
Variable	**Symbol**	**Mean**	**SD**	**Percentile 50th**	**Min.**	**Max.**
Profit before tax	PBT	23.971	2.048	24.752	−17.302	149.949
Price of borrowed funds	p1	0.021	0.012	0.019	0.006	0.038
Price of labour	p2	0.058	0.019	0.056	0.034	0.092
Price of physical capital	p3	1.217	0.091	1.153	0.333	2.501
Total loans	q1	1194.988	112.513	1203.194	156.687	6209.267
Total earning assets	q2	631.299	34.427	634.498	49.506	3345.217
Off balance sheet items	q3	1671.988	184.738	1652.617	72.957	11356.95
Credit Risk	σ1	0.015	0.021	0.014	0.000	0.083
Leverage	σ2	10.751	0.837	10.462	6.464	14.727
Variance of profits	VarProf	0.012	0.031	0.014	0.000	0.049
Return on equity	ROE	0.051	0.137	0.087	−1.245	2.148
Return on assets	ROA	0.006	0.019	0.008	−0.118	0.202

Note: This table refers to 46,553 bank-time period observations for 7180 US commercial banks between 2003 and 2012. Panel A provides definitions for all variables used in our analysis. Panel B reports descriptive statistics of the kernel variables used in the estimation of the stochastic profit frontier model. All variables are deflated using 2005 as a base year. Kernel variables consist of the dependent variable, that is, profits before tax (PBT), inputs prices (p), output quantities (q) and the two risk indicators (σ). We also present as well descriptive statistics for three additional variables, that is, Variance of Profits (VarProf) that we use as an alternative indicator of risk; as well as return on equity (ROE) and return on assets (ROA) that we use as two alternative indicators of profitability. PBT, q1, q2, q3 are in millions of $US.

indicators moved in opposite directions: the coefficient of the variance of profit increased and that of the leverage decreased. The *ex-post* indicator of risk also became more significant in this period (see Table 2). Similar qualitative results hold in the last period of our investigation for both leverage and variance of profits but not for credit risk. So, a general result of this empirical analysis is the opposite impact of the two *ex-ante* risk indicators on profit efficiency. It is noteworthy that leverage remained the most important risk determinant of profit efficiency throughout the whole sample period (see Table 2). This finding suggests that leverage does shape the level of efficiency of the bank, and we should include this long run measure of risk into the profit efficiency indicator.

6.1 | Profit efficiency scores

We now turn our focus to the first step of our empirical methodology. Specifically, we test the robustness of our profit efficiency indicators by examining the empirical

TABLE 2 Estimation of profit efficiency: Credit risk and leverage and variance of profits.

lnPBT	2003 Coefficient (standard error)	2006 Coefficient (standard error)	2009 Coefficient (standard error)	2012 Coefficient (standard error)
lnp1	0.012	0.168***	0.093	0.081
	(0.051)	(0.047)	(0.034)	(0.021)
lnp2	0.316***	0.106*	0.117***	0.226***
	(0.024)	(0.033)	(0.033)	(0.027)
lnq1	0.362***	0.407***	0.109***	0.129***
	(0.024)	(0.021)	(0.019)	(0.017)
lnq2	0.179***	0.114***	0.077***	0.093**
	(0.023)	(0.029)	(0.033)	(0.026)
lnq3	0.382	0.416***	0.621***	0.785***
	(0.077)	(0.091)	(0.083)	(0.047)
Trend	0.189	0.214	0.261	0.226
	(0.031)	(0.024)	(0.019)	(0.017)
0.5 $(\ln p1)^2$	−0.012	0.087***	0.021	−0.016
	(0.006)	(0.017)	(0.009)	(0.004)
0.5 $(\ln p2)^2$	0.066***	0.114***	0.057***	0.036***
	(0.013)	(0.017)	(0.009)	(0.008)
0.5 $(\ln q1)^2$	0.057**	0.032	0.081***	0.049***
	(0.016)	(0.019)	(0.011)	(0.013)
0.5 $(\ln q2)^2$	0.039***	0.047***	0.026***	0.022***
	(0.004)	(0.006)	(0.007)	(0.009)
0.5 $(\ln q3)^2$	0.094	0.026***	0.032***	0.021***
	(0.015)	(0.018)	(0.019)	(0.017)
0.5 $(\text{Trend})^2$	0.315	0.329	0.284	0.293
	(0.024)	(0.08)	(0.025)	(0.017)
lnp1*lnp2	0.031	−0.062***	−0.036***	0.019
	(0.011)	(0.012)	(0.009)	(0.011)
lnq1*lnq2	−0.032***	−0.033***	−0.031***	−0.023***
	(0.006)	(0.011)	(0.007)	(0.008)
lnq1*lnq3	0.042***	0.056***	−0.043	0.038***
	(0.007)	(0.005)	(0.006)	(0.002)
lnq2*lnq3	0.012	0.009	0.027***	0.014**
	(0.003)	(0.009)	(0.007)	(0.006)
lnp1*lnq1	0.033**	0.018	−0.026*	−0.009
	(0.006)	(0.009)	(0.006)	(0.008)
lnp1*lnq2	−0.014	0.009	−0.026***	−0.013**
	(0.005)	(0.009)	(0.006)	(0.004)
lnp1*lnq3	0.042***	0.026	−0.026	−0.011
	(0.005)	(0.018)	(0.005)	(0.009)
lnp2*lnq1	0.067***	0.092***	−0.008	0.026**
	(0.006)	(0.012)	(0.006)	(0.005)
lnp2*lnq2	0.026***	0.018*	0.031***	0.019**
	(0.003)	(0.008)	(0.002)	(0.008)

TABLE 2 (Continued)

lnPBT	2003 Coefficient (standard error)	2006 Coefficient (standard error)	2009 Coefficient (standard error)	2012 Coefficient (standard error)
lnp2*lnq3	0.026***	0.008	0.023***	0.012***
	(0.004)	(0.006)	(0.005)	(0.006)
lnNPI	−0.123***	−0.164***	−0.033***	−0.083***
	(0.018)	(0.022)	(0.009)	(0.012)
lnCR	−0.011***	−0.019***	−0.024***	−0.022***
	(0.005)	(0.005)	(0.005)	(0.006)
lnLEV	−0.037***	−0.029***	−0.021***	−0.019***
	(0.018)	(0.021)	(0.012)	(0.011)
lnVarPr	0.026***	0.015***	0.017***	0.021***
	(0.002)	(0.002)	(0.002)	(0.002)
constant	0.437***	0.292***	0.088	0.513***
	(0.049)	(0.056)	(0.032)	(0.041)
lnsig2v	−5.764***	−5.074***	−4.922***	−5.617***
	(0.058)	(0.089)	(0.021)	(0.086)
lnsig2u	−4.171***	−4.328***	−16.072	−4.912***
	(0.053)	(0.124)	(0.143)	(0.139)
Observations	4818	4724	4206	3692

Note: The table reports profit efficiency estimation results adjusted for three different indicators of risk (i.e., credit variable is the banks' risk, leverage, and variance of profit) in four distinct time periods, where the dependent profits before tax (PBT). Robust standard errors adjusted for bank clustering are reported in parentheses. *, ** and *** denote significance at 10%, 5% and 1% level, respectively.

TABLE 3 Number of banks (halftiles).

Panel A: Pre-crisis—2006 versus 2003											
2003	**PE via credit risk**		**2003**	**PE via credit risk and leverage**		**2003**	**PE via variance of profits**		**2003**	**PE via variance of profits and leverage**	
1	1233	305	**1**	1443	95	**1**	1132	406	**1**	1364	174
2	305	1233	**2**	95	1443	**2**	406	1132	**2**	174	1364
2006	**1**	**2**	**2006**	**1**	**2**	**2006**	**1**	**2**	**2006**	**1**	**2**
Panel B: During-crisis—2009 versus 2006											
2006	**PE via credit risk**		**2006**	**PE via credit risk and leverage**		**2006**	**PE via variance of profits**		**2006**	**PE via variance of profits and leverage**	
1	1054	484	**1**	1372	166	**1**	913	625	**1**	1237	301
2	484	1054	**2**	166	1372	**2**	625	913	**2**	301	1237
2009	**1**	**2**	**2009**	**1**	**2**	**2009**	**1**	**2**	**2009**	**1**	**2**
Panel C: Post-crisis—2012 versus 2009											
2009	**PE via credit risk**		**2009**	**PE via credit risk and leverage**		**2009**	**PE via variance of profits**		**2009**	**PE via variance of profits and leverage**	
1	1173	365	**1**	1426	112	**1**	1054	484	**1**	1329	209
2	365	1173	**2**	112	1426	**2**	484	1054	**2**	209	1329
2012	**1**	**2**	**2012**	**1**	**2**	**2012**	**1**	**2**	**2012**	**1**	**2**

Note: This table presents information about the number of banks that changed their relative position with respect to their profit efficiency ranking deriving by four alternative risk-adjusted profit efficiency indexes, that is, a. credit risk, b. credit risk and leverage, c. variance of profits, d. variance of profits and leverage. Panel A, B and C, refers to the 'pre-crisis', 'during crisis' and 'post-crisis' period, respectively. Halftile '1' and '2' consist of banks with the lowest and highest profit efficiency levels, respectively.

TABLE 4 Number of banks (quartiles).

Panel A: Pre-crisis—2006 versus 2003																			
2003	**PE via credit risk**				**2003**	**PE via credit risk and leverage**				**2003**	**PE via variance of profits**				**2003**	**PE via variance of profits and leverage**			
1	487	151	81	49	**1**	662	76	23	5	**1**	398	208	95	68	**1**	569	116	78	17
2	173	463	77	60	**2**	61	669	33	8	**2**	184	421	83	82	**2**	115	557	56	18
3	68	84	466	149	**3**	39	18	647	65	**3**	120	81	385	183	**3**	72	44	561	116
4	43	73	142	510	**4**	4	7	70	689	**4**	64	63	207	434	**4**	14	68	112	563
2006	**1**	**2**	**3**	**4**	**2006**	**1**	**2**	**3**	**4**	**2006**	**1**	**2**	**3**	**4**	**2006**	**1**	**2**	**3**	**4**
Panel B: During crisis—2009 versus 2006																			
2006	**PE via credit risk**				**2006**	**PE via credit risk and leverage**				**2006**	**PE via credit risk**				**2006**	**PE via variance of profits and leverage**			
1	401	205	104	60	**1**	618	91	49	8	**1**	309	251	119	91	**1**	504	134	102	31
2	207	395	88	79	**2**	83	607	31	51	**2**	245	312	112	105	**2**	136	479	61	96
3	107	86	407	165	**3**	59	26	593	92	**3**	137	121	301	208	**3**	103	59	492	116
4	55	82	169	466	**4**	7	45	98	618	**4**	79	90	234	362	**4**	27	98	119	519
2009	**1**	**2**	**3**	**4**	**2009**	**1**	**2**	**3**	**4**	**2009**	**1**	**2**	**3**	**4**	**2009**	**1**	**2**	**3**	**4**
Panel C: Post-crisis—2012 versus 2009																			
2009	**PE via Credit Risk**				**2009**	**PE via credit risk and leverage**				**2009**	**PE via Credit Risk**				**2009**	**PE via variance of profits and leverage**			
1	458	131	124	55	**1**	648	84	29	7	**1**	326	178	174	89	**1**	553	107	82	23
2	123	419	109	117	**2**	59	647	48	17	**2**	174	304	119	175	**2**	93	512	84	85
3	124	111	416	123	**3**	56	23	633	60	**3**	186	109	297	178	**3**	95	69	517	90
4	59	115	121	471	**4**	8	16	59	682	**4**	82	181	179	325	**4**	25	86	87	568
2012	**1**	**2**	**3**	**4**	**2012**	**1**	**2**	**3**	**4**	**2012**	**1**	**2**	**3**	**4**	**2012**	**1**	**2**	**3**	**4**

Note: This table presents information about the number of banks that changed their relative position with respect to their profit efficiency ranking deriving by four alternative risk-adjusted profit efficiency indexes, that is, a. credit risk, b. credit risk and leverage, c. variance of profits, d. variance of profits and leverage. Panel A, B and C, refers to the 'pre-crisis', 'during crisis' and 'post-crisis' period respectively. Quartile '1' and '4' consist of banks with the lowest and highest profit efficiency levels, respectively.

TABLE 5 Number of banks (deciles).

Panel A: Pre-crisis—2006 versus 2003																					
2003	**PE via credit risk**										**2003**	**PE via credit risk and leverage**									
1	202	13	12	13	11	13	12	10	13	9	**1**	269	5	4	5	5	4	5	4	3	2
2	12	194	12	13	11	13	11	12	13	12	**2**	6	270	5	4	4	5	4	4	3	3
3	11	13	198	13	12	13	13	12	12	12	**3**	4	4	269	4	4	5	4	4	4	4
4	12	13	12	191	14	13	13	14	14	11	**4**	4	4	5	270	5	3	5	5	4	4
5	11	13	13	13	197	13	13	12	13	11	**5**	5	4	4	6	270	7	2	4	4	4
6	14	11	12	12	16	192	13	13	11	12	**6**	5	5	4	4	4	267	4	4	4	6
7	11	12	13	14	12	13	195	15	13	12	**7**	4	5	5	4	4	5	266	5	4	5
8	11	14	12	11	12	13	15	197	13	11	**8**	4	4	4	4	4	5	4	268	4	6
9	12	11	14	11	12	13	13	12	195	14	**9**	3	4	4	4	4	3	5	6	271	4
10	9	12	11	14	12	12	12	11	12	203	**10**	3	3	4	4	4	4	6	3	7	270
2006	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**2006**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Panel A: Pre-crisis—2006 versus 2003																					
2003	**PE via variance of profits**										**2003**	**PE via variance of profits and leverage**									
1	162	19	20	17	13	16	18	16	14	12	**1**	238	8	9	8	7	9	7	8	8	6
2	17	160	17	19	15	16	17	16	16	13	**2**	7	241	8	7	7	8	7	8	8	7
3	18	19	161	16	13	16	17	16	16	15	**3**	7	9	234	9	8	8	9	7	8	8
4	19	15	16	165	16	15	16	15	14	18	**4**	9	7	8	237	8	7	8	8	7	8
5	15	15	14	18	164	16	17	17	15	17	**5**	9	8	8	8	240	7	7	7	7	7
6	16	16	16	16	17	163	17	15	16	15	**6**	8	8	8	8	8	237	8	7	7	8
7	19	16	16	13	15	19	164	15	15	17	**7**	7	7	8	8	7	8	241	7	7	7
8	15	17	14	16	17	17	14	166	16	17	**8**	9	7	8	8	7	7	7	241	7	7
9	15	14	18	18	19	12	13	13	167	21	**9**	8	7	7	7	8	8	7	7	241	7
10	12	14	15	13	19	15	15	19	21	161	**10**	7	7	9	7	8	8	7	7	7	242
2006	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**2006**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**

Panel B: During crisis—2009 versus 2006																					
2006	**PE via credit risk**										**2006**	**PE via credit risk and leverage**									
1	159	18	14	18	16	18	16	17	16	14	**1**	249	7	7	6	7	6	6	6	7	5
2	18	160	17	16	18	16	16	16	17	15	**2**	7	250	7	6	6	6	6	7	6	6
3	17	16	155	18	18	16	16	20	18	16	**3**	7	7	248	6	7	8	5	6	6	7
4	16	17	19	161	17	15	16	15	17	15	**4**	6	6	7	247	7	6	8	7	6	7
5	17	16	19	19	160	17	15	16	15	15	**5**	7	6	7	7	249	6	6	7	6	7
6	16	17	18	15	16	161	17	15	16	18	**6**	7	8	6	8	7	248	8	6	6	5
7	17	17	17	16	16	16	161	16	17	15	**7**	8	7	7	7	6	8	246	7	7	6
8	15	17	15	15	15	17	19	162	16	15	**8**	6	5	7	6	7	6	7	250	7	8
9	16	16	19	16	16	17	16	16	158	16	**9**	6	6	6	6	6	7	8	7	251	4
10	14	15	15	16	15	16	16	16	17	165	**10**	4	6	6	7	7	6	8	7	5	251
2009	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**2009**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Panel B: During crisis—2009 versus 2006																					
2006	**PE via variance of profits**										**2006**	**PE via variance of profits and leverage**									
1	121	21	21	21	21	23	22	21	19	18	**1**	203	13	13	12	13	11	10	11	11	10
2	22	122	21	23	19	20	21	21	21	19	**2**	14	198	14	12	11	12	12	13	12	11
3	21	22	116	24	23	21	20	22	19	20	**3**	12	13	195	14	12	13	11	13	11	12
4	21	22	25	116	21	22	22	21	21	20	**4**	12	12	14	200	14	12	11	11	12	11
5	22	20	21	21	124	20	20	20	19	21	**5**	12	12	13	12	198	15	12	13	11	11
6	20	20	23	22	21	117	24	21	19	20	**6**	12	11	12	13	13	197	13	11	12	13
7	20	21	21	19	22	23	120	21	21	20	**7**	11	12	13	11	13	12	203	11	12	11
8	21	20	20	20	20	21	20	121	23	21	**8**	11	12	11	12	11	12	13	201	13	12
9	20	21	21	21	19	20	20	20	122	22	**9**	11	12	12	12	11	12	12	12	201	13
10	19	19	20	21	19	21	19	20	22	124	**10**	9	12	12	11	12	12	11	12	11	202
2009	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**2009**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**

Panel C: Post-crisis—2012 versus 2009																					
2009	**PE via credit risk**										**2009**	**PE via credit risk and leverage**									
1	182	14	15	15	13	13	14	15	13	12	1	259	8	6	5	5	7	6	4	5	3
2	14	181	17	13	13	13	14	16	14	13	2	7	259	7	5	5	6	5	4	4	4
3	15	16	183	14	12	13	14	14	14	14	3	6	6	262	7	5	4	4	5	4	5
4	14	13	14	182	15	13	14	14	13	14	4	5	6	6	262	5	4	5	4	6	4
5	15	14	13	15	180	14	13	14	13	14	5	6	7	4	5	261	6	6	5	5	4
6	14	13	13	14	15	183	16	14	13	13	6	5	5	5	5	5	262	5	6	5	5
7	15	14	14	14	14	16	181	14	15	13	7	5	5	5	6	7	6	261	4	4	4
8	13	16	13	15	13	15	17	177	15	15	8	5	4	4	5	4	5	7	265	5	5
9	13	14	13	13	13	14	13	14	185	16	9	6	4	4	4	5	4	6	5	263	6
10	11	13	14	13	16	15	13	15	14	183	10	3	4	5	4	6	4	4	5	6	266
2012	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**2012**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Panel C: Post-crisis—2012 versus 2009																					
2009	**PE via variance of profits**										**2009**	**PE via variance of profits and leverage**									
1	132	24	21	19	20	17	19	20	18	15	**1**	222	11	10	9	9	11	9	9	9	7
2	24	129	24	20	20	19	20	18	18	16	**2**	10	225	11	10	9	9	9	8	9	9
3	19	21	133	23	19	18	17	20	19	17	**3**	10	10	220	13	9	9	9	9	9	10
4	21	21	21	133	21	18	17	19	19	17	**4**	10	9	13	221	10	10	9	9	9	8
5	20	18	18	23	132	21	20	19	17	19	**5**	9	9	9	11	221	12	9	8	10	9
6	22	19	19	20	25	133	19	17	16	18	**6**	9	10	9	8	11	221	11	10	10	9
7	18	20	18	19	19	25	133	23	16	20	**7**	10	9	9	9	9	10	223	10	9	10
8	17	20	19	16	17	20	23	131	25	21	**8**	9	9	8	9	9	9	11	220	14	10
9	18	19	16	16	19	19	23	23	133	23	**9**	9	8	9	9	10	9	9	13	221	10
10	15	16	17	18	17	16	20	19	27	141	**10**	8	9	10	9	9	9	9	11	9	224
2012	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**2012**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**

Note: This table presents information about the number of banks that changed their relative position with respect to their profit efficiency ranking deriving by four alternative risk-adjusted profit efficiency indexes, that is, a. credit risk, b. credit risk and leverage, c. variance of profits, d. variance of profits and leverage. Panel A, B and C, refers to the 'pre-crisis', 'during crisis' and 'post-crisis' period respectively. Decile '1' and '10' consists of banks with the lowest and highest profit efficiency levels, respectively.

TABLE 6 Explanatory power.

lnROE	Credit risk Coefficient (standard error)	Credit risk with leverage Coefficient (standard error)	Variance of profits Coefficient (standard error)	Variance of profits with leverage Coefficient (standard error)
Panel A: Pre-crisis – 2003				
PE_2003	4.941***	7.518***	2.294***	5.592***
	(0.059)	(0.083)	(0.017)	(0.083)
F-stat	1238.262	2439.174	861.233	1.914.312
adjR^2	0.826	0.964	0.793	0.883
AIC	−9782.318	−11816.421	−9236.796	−11136.914
Observations	3076	3076	3076	3076
Panel B: Pre-crisis—2006				
PE_2006	14.613***	14.262***	3.913***	3.843***
	(0.161)	(0.172)	(0.027)	(0.067)
F-stat	1816.431	2894.677	1372.146	1982.552
adjR^2	0.873	0.973	0.845	0.942
AIC	−10369.213	−12486.299	−10280.344	−12113.811
Observations	3076	3076	3076	3076
Panel C: During crisis—2009				
PE_2009	6.381***	7.683***	5.234***	7.081***
	(0.267)	(0.186)	(0.382)	(0.151)
F-stat	4952.926	7296.174	3783.461	5942.883
adjR^2	0.879	0.966	0.837	0.917
AIC	−12156.443	−15163.422	−11316.957	−14152.151
Observations	3076	3076	3076	3076
Panel D: Post-crisis —2012				
PE_2012	5.693***	7.741***	2.328***	6.417***
	(0.029)	(0.046)	(0.019)	(0.022)
F-stat	1056.631	2365.897	781.346	1763.181
adjR^2	0.837	0.936	0.781	0.881
AIC	−12019.221	−13109.749	−10377.188	−12391.145
Observations	3076	3076	3076	3076

Note: This table presents results for the ordinary least squares (OLS) regressions where the dependent (i.e., return on equity) is a proxy for bank profitability and one of the regressors (to shorten the size of the table we do not report the results of the parameters of the translog profit function—they are available upon request) is the profit efficiency level derived by four alternative risk-adjusted profit efficiency indexes, that is, a. credit risk, b. credit risk and leverage, c. variance of profits, d. variance of profits and leverage. Panels A and B refer to the 'pre-crisis', whereas Panels C and D refer to the 'during crisis' and 'post-crisis' period respectively. Robust standard errors adjusted for bank clustering are reported in parentheses. *, ** and *** denote significance at 10%, 5%, and 1% level respectively.

evidence presented in the three different Markov transition matrices in terms of range.

Tables 3, 4, 5 display the exact number of banks that changed position with respect to the 'pre-crisis', 'during-crisis' and 'post-crisis' state of the economy and among the three Markov transition matrices; half-tiles, quartiles, and deciles, respectively. The empirical evidence demonstrates that in all three economic periods (i.e., 2003 vs. 2006; 2006 vs. 2009; 2009 vs. 2012) there is less deviation in the ordering of banks with respect to their efficiency scores that derive from both our proposed risk-adjusted profit efficiency indexes compared to those currently used in the literature that do not account for the leverage position of the bank. This

TABLE 7 Test of equivalence of the explanatory power—Regression Model.

	2003		2006		2009		2012	
	Coefficient	***p*-value**	**Coefficient**	***p*-value**	**Coefficient**	***p*-value**	**Coefficient**	***p*-value**
Credit risk versus credit risk with leverage	0.218	0.000	0.473	0.416	0.377	0.000	0.515	0.000
Credit risk versus variance of profits	1.729	0.003	1.306	0.001	1.488	0.582	1.711	0.386
Credit risk versus variance of profits with leverage	0.466	0.008	0.519	0.002	0.783	0.000	0.713	0.000
Credit risk with leverage versus variance of profits	2.182	0.000	1.633	0.007	1.502	0.000	1.604	0.000
Credit risk with leverage versus variance of profits with leverage	0.306	0.319	0.438	0.000	0.237	0.207	0.441	0.259
Variance of profits versus variance of profits with leverage	0.783	0.000	0.647	0.000	0.877	0.000	0.837	0.000

Note: This table report the results from the Vuong (1989) test, for panel data (see Wooldridge, 2010), for equivalence of the explanatory power on each possible pairwise regression models, where the null hypothesis states that the models are indistinguishable.

result is unequivocally supported in all three different Markov-matrices as well. The superiority of the risk-adjusted profit index becomes more apparent when we examine two fairly extreme scenarios of banks profit efficiency transition. To be more precise, we focus on how many banks move from the top 50% to the lowest position in terms of efficiency scores in the preceding time period for each respective matrix, that is, from deciles 10, 9, 8, 7, 6; from quartiles 4, 3; and from half-tile 2 in time t, to the first (i.e., 1) decile/quartile/half-tile in time $t + 1$. The results indicate that fewer banks followed this extreme transition when their profit efficiency is estimated by the two proposed risk and stability adjusted profit efficiency indicators. This holds when we account for the reverse movement scenario as well, that is, from the lowest 50% to the top 10%, 25% and 50% for deciles, quartiles and half-tiles respectively. It is worth noting that when we examine the difference in the number of banks that move in the two opposite extremes (i.e., from the most efficient position to the least efficient and vice-versa) with respect to each index, each Markov matrix (i.e., decile/quartile/half-tile) generates the same result, depending on the economic conditions. Precisely, the difference among all four profit indexes in each one of the three Markov Transition Matrices is larger in the 'pre' versus 'during' the crisis comparison (i.e., 2006 vs. 2009), followed by the 'during' versus 'post' crisis comparison (i.e., 2009 vs. 2012). By contrast, the quiet economic periods (i.e., 2003 vs. 2006) exhibit the smallest deviation in the ordering of banks to the different profit efficiency classes.

6.2 | Explanatory and predictive power

Next, we address the effectiveness of the efficiency indicators proposed in this study. First, we compare the four banking efficiency indicators with respect to their explanatory power. These indicators are built up assuming alternative measures of risk. The first and our preferred efficiency indicator is the one that accounts for both an *ex-post* and a long run *ex-ante* indicator of risk (*sredit rish and leverage*). The second alternative efficiency indicator includes only the *ex-post* risk indicator (*sredit rish*). In the third alternative efficiency, indicator risk is measured by a short run *ex-ante* indicator of risk (*varianse of prof it*). The last alternative efficient indicator includes both a short run and a long run *ex-ante* indicator of risk (*varianse of profits and leverage*).

Table 6 reports the empirical findings. Panels A and B refer to the 'pre-crisis', whereas Panels C and D refer to the 'during crisis' and 'post-crisis' period respectively. Albeit all indexes are statistically significant in explaining banks' profits, we note that the model that includes the risk (*ex-post*) and stability (leverage) adjusted profit efficiency index has smaller value in the information criterion metric (AIC), higher value in the fitness of data metric (adjR^2) and higher value regarding the overall significance of the model metric (F-stat). This is followed by the index that accounts for both short run and a long run *ex-ante* indicator of risk, whereas the index that includes only an *ex-post* risk indicator or an (short run) *ex-ante* risk indicator are ranked third and four respectively, against the same aforementioned metrics. Similar results are derived in all four time periods under examination.

TABLE 8 Predictive power.

lnROE	Credit risk Coefficient (standard error)	Credit risk with leverage Coefficient (standard error)	Variance of profits Coefficient (standard error)	Variance of profits with leverage Coefficient (standard error)
Panel A: Pre-crisis—2006 versus 2003				
PE_2003	3.628***	4.649***	1.217***	0.916***
	(0.062)	(0.019)	(0.073)	(0.059)
Constant	−2.815***	−3.118***	−0.826***	−0.923***
	(0.061)	(0.017)	(0.043)	(0.056)
F-stat	436.216	739.371	388.615	572.687
adjR^2	0.623	0.769	0.571	0.608
AIC	−4218.552	−6015.263	−4216.163	−5016.117
MSE	1.181	0.216	1.318	0.673
MAE	1.057	0.172	1.149	0.638
Observations	3076	3076	3076	3076
Panel B: During crisis—2009 versus 2006				
PE_2006	4.266***	4.674***	1.218***	1.093***
	(0.069)	(0.048)	(0.051)	(0.063)
Constant	−2.631***	−2.726***	−0.547***	−0.157***
	(0.014)	(0.037)	(0.061)	(0.077)
F-stat	265.943	377.121	234.676	319.332
adjR^2	0.539	0.638	0.429	0.537
AIC	−4752.014	−6369.227	−4731.923	−5905.127
MSE	1.462	0.469	1.563	0.917
MAE	1.108	0.367	1.528	0.816
Observations	3076	3076	3076	3076
Panel C: Post-crisis—2012 versus 2009				
PE_2009	3.267***	3.697***	0.826***	1.178***
	(0.064)	(0.072)	(0.083)	(0.071)
Constant	−2.617***	−2.846***	−0.492***	−0.318***
	(0.016)	(0.042)	(0.088)	(0.037)
F-stat	368.177	564.717	319.332	456.143
adjR^2	0.586	0.691	0.472	0.583
AIC	−4436.928	−6183.648	−4538.163	−5615.015
MSE	1.362	0.316	1.436	0.757
MAE	1.086	0.219	1.269	0.739
Observations	3076	3076	3076	3076

Note: This table presents results for the ordinary least squares (OLS) regressions where the dependent variable ROE (i.e., return on equity) is a proxy for bank profitability and one of the regressors (to shorten the size of the table we do not report the results of the parameters of the translog profit function—they are available upon request) is the profit efficiency level, in time 't-3', derived by four alternative risk-adjusted profit efficiency indexes, that is, a. credit risk, b. credit risk and leverage, c. variance of profits, d. variance of profits and leverage. Panel A, B and C, refers to the 'pre-crisis', 'during crisis' and 'post-crisis' period, respectively. The predictive power of the model is captured by the two conventional forecasting measurement errors, that is, the 'MSE' and 'MAE', that stand for the 'Mean Square Error' and the 'Mean Absolutely Error' respectively. Robust standard errors adjusted for bank clustering are reported in parentheses. *, ** and *** denote significance at 10%, 5% and 1% level, respectively.

Regarding the economic significance of the aforementioned results, we find that moving profit efficiency during normal times from 0 to 1, that is, from the most inefficient to the most efficient, increases the bank's profits during the four different time periods on average by 64.3% (from 0.42 to 0.69) for the index that accounts

TABLE 9 Diebold-Mariano.

	Panel A: Pre-crisis—2006 versus 2003					
	MSE			MAE		
	DM-statistic	*p*-value	Outcome	DM-statistic	*p*-value	Outcome
Credit risk versus credit risk with leverage	3.294	0.000	Credit risk with l everage	4.153	0.000	Credit risk with leverage
Credit risk versus variance of profits	5.698	0.000	Credit risk	4.237	0.000	Credit risk
Credit risk versus variance of profits with leverage	5.388	0.000	Variance of profits with leverage	5.348	0.000	Variance of profits with leverage
Credit risk with leverage versus variance of profits	5.262	0.000	Credit risk with leverage	4.646	0.000	Credit risk with leverage
Credit risk with leverage versus variance of profits with leverage	4.348	0.000	Credit risk with leverage	5.729	0.000	Credit risk with leverage
Variance of profits versus variance of profits with leverage	4.637	0.000	Variance of profits with leverage	5.729	0.000	Variance of profits with leverage
	Panel B: During crisis—2009 versus 2006					
	MSE			**MAE**		
	DM-statistic	***p*-value**	**Outcome**	**DM-statistic**	***p*-value**	**Outcome**
Credit risk versus credit risk with leverage	1.628	0.631	Equal	1.649	0.157	Equal
Credit risk versus variance of profits	3.358	0.000	Credit risk	3.693	0.000	Credit risk
Credit risk versus variance of profits with leverage	3.158	0.000	Variance of profits with leverage	4.182	0.000	Variance of profits with leverage
Credit risk with leverage versus variance of profits	4.582	0.000	Credit risk with leverage	5.196	0.000	Credit risk with leverage
Credit risk with leverage versus variance of profits with leverage	0.624	0.369	Equal	0.917	0.297	Equal
Variance of profits versus variance of profits with leverage	1.271	0.371	Equal	1.672	0.321	Equal
	Panel C: Post-crisis—2012 versus 2009					
	MSE			**MAE**		
	DM-statistic	***p*-value**	**Outcome**	**DM-statistic**	***p*-value**	**Outcome**
Credit risk versus credit risk with leverage	2.693	0.000	Credit risk with leverage	3.341	0.000	Credit risk with leverage
Credit risk versus variance of profits	3.918	0.000	Credit risk	3.692	0.000	Credit risk
Credit risk versus variance of profits with leverage	4.152	0.000	Variance of profits with leverage	4.726	0.000	Variance of profits with leverage
Credit risk with leverage versus variance of profits	5.643	0.000	Credit risk with leverage	5.372	0.000	Credit risk with leverage
Credit risk with leverage versus variance of profits with leverage	1.931	0.308	Equal	2.956	0.238	Equal

(Continues)

TABLE 9 (Continued)

	Panel C: Post-crisis—2012 versus 2009					
	MSE			MAE		
	DM-statistic	*p*-value	Outcome	DM-statistic	*p*-value	Outcome
Variance of profits versus variance of profits with leverage	5.261	0.000	Variance of profits with leverage	5.486	0.000	Variance of profits with leverage

Note: This table report the results of the Diebold and Mariano (1995) test of the forecasting accuracy on each possible pairwise regression models and indicate which is the better predictor between the two under consideration. The null hypothesis states that the models under consideration have the same predictive accuracy. 'Equal' refers to those cases where the difference of the forecasting power between the two models that include either one of the two profit efficiency indexes is not statistically significant. Panel A, B and C, refers to the 'pre-crisis', 'during crisis' and 'post-crisis' period, respectively.

TABLE 10 Model confidence set (MCS)—Predictive power.

	MSE			MAE		
	Coefficient	*p*-value	Rank	Coefficient	*p*-value	Rank
Panel A: Pre-crisis—2006 versus 2003						
Credit risk	1.292	0.617	3	1.132	0.482	3
Credit risk with leverage	0.671	1.000	1	0.638	1.000	1
Variance of profits	1.729	0.361	4	1.383	0.269	4
Variance of profits with leverage	0.923	1.000	2	0.828	1.000	2
Panel B: During crisis—2009 versus 2006						
Credit risk	1.789	0.057	3	1.429	0.011	3
Credit risk with leverage	0.926	1.000	1	0.806	1.000	2
Variance of profits	2.029	0.019	4	1.739	0.003	4
Variance of profits with leverage	1.362	1.000	2	1.183	1.000	1
Panel C: Post-crisis—2012 versus 2009						
Credit risk	1.427	0.239	4	1.363	0.163	3
Credit risk with leverage	0.836	1.000	1	0.718	1.000	2
Variance of profits	1.918	0.115	3	1.583	0.037	4
Variance of profits with leverage	1.173	1.000	2	1.091	1.000	1

Note: This table presents the Hansen et al. (2011) Model Confidence Set (MCS) tests results of two conventional forecasting measurement errors, that is, the 'MSE' and 'MAE', that stand for the 'Mean Square Error' and the 'Mean Absolutely Error' respectively. The null hypothesis states that the models under consideration have Equal Predictive Ability (EPA). The table also reports, for each one of the forecasting measurement error, the final ranked position of the four alternative risk-adjusted profit efficiency indexes, that is, a. credit risk, b. credit risk and leverage, c. variance of profits, d. variance of profits and leverage. Panel A, B and C, refers to the 'pre-crisis', 'during crisis' and 'post-crisis' period respectively.

for credit risk and leverage, by 48.6% (from 0.35 to 0.52) for the index that accounts for variance of profits and leverage, by 41.4% (from 0.29 to 0.41) for the index that accounts for credit risk only and by 37%.(from 0.27 to 0.37) for the index that accounts for just the variance of profits.

In order to test the statistical significance of our results, we use the Vuong (1989) test, for panel data (see Wooldridge, 2010), for equivalence of explanatory power in each pair-model combination for all four different time periods, where the null hypothesis is that the models are indistinguishable. In Table 7 we report that in the majority of cases the difference in explanatory power between the two models under consideration is statistically significant, highlighting the different contribution that each one of the profit efficiency indexes has in explaining a bank's profits.[8] These findings further strengthen our argument regarding the imperative importance to account for leverage in the measurement of profit efficiency.

Next, we test the efficiency of the alternative profit efficiency indicators by estimating the predictive power of the profits in 3 years' time. We claim that the profit efficiency indicator (7) that accounts for stability is more appropriate to estimate banking efficiency in the long run, and that the model including this indicator of efficiency is a better predictor of future profits than the econometric models using alternative profit efficiency

TABLE 11 Predictive power—Solvent.

lnROE	Credit risk Coefficient (standard error)	Credit risk with leverage Coefficient (standard error)	Variance of profits Coefficient (standard error)	Variance of profits with leverage Coefficient (standard error)
Panel A: Pre-crisis—2006 versus 2003				
PE_2003	1.816***	1.982***	0.863***	0.917***
	(0.049)	(0.093)	(0.073)	(0.035)
F-stat	364.815	638.344	318.175	492.657
adjR^2	0.618	0.769	0.511	0.672
AIC	−7295.652	−9391.944	−6861.829	−8264.641
MSE	1.625	0.728	1.764	0.953
MAE	1.431	0.334	1.403	0.679
Observations	2060	2060	2060	2060
Panel B: During crisis—2009 versus 2006				
PE_2006	1.654***	1.156***	0.761***	0.812***
	(0.041)	(0.073)	(0.064)	(0.071)
F-stat	264.869	421.718	215.553	315.291
adjR^2	0.521	0.614	0.405	0.513
AIC	−6852.155	−8816.157	−5515.89	−7615.153
MSE	2.416	1.269	2.742	1.561
MAE	2.161	0.816	2.428	1.137
Observations	2060	2060	2060	2060
Panel C: Post crisis—2012 versus 2009				
PE_2009	1.806***	1.793***	1.525***	1.522***
	(0.054)	(0.016)	(0.084)	(0.018)
F-stat	315.261	517.155	284.997	384.148
adjR^2	0.581	0.693	0.488	0.619
AIC	−7045.264	−9131.416	−5906.177	−7921.161
MSE	1.959	1.083	2.109	1.382
MAE	1.715	0.535	1.924	0.917
Observations	2060	2060	2060	2060

Note: This table presents results for the ordinary least squares (OLS) regressions, that remained solvent during the financial crisis, where the dependent variable ROE (i.e., return on equity) is a proxy for bank profitability and one of the regressors (to shorten the size of the table we do not report the results of the parameters of the translog profit function—they are available upon request) is the profit efficiency level, in time 't-3', derived by four alternative risk-adjusted profit efficiency indexes, that is, a. credit risk, b. credit risk and leverage, c. variance of profits, d. variance of profits and leverage. Panel A, B and C, refers to the 'pre-crisis', 'during-crisis' and 'post-crisis' period respectively. The predictive power of the model is captured by the two conventional forecasting measurement errors, that is, the 'MSE' and 'MAE', that stand for the 'Mean Square Error' and the 'Mean Absolutely Error' respectively. Robust standard errors adjusted for bank clustering are reported in parentheses. *, ** and *** denote significance at 10%, 5%, and 1% level, respectively.

indicators. Table 8 reports the results of the econometric investigation for all three different states of the economy; 'pre-crisis', 'during-crisis', 'post-crisis', respectively.[9]

As far as the first time period is concerned, where we use the estimated values of 2003 to examine how well they explain the 'future' banks' profits of 2006, the results are in favour of the two proposed indexes, as they exhibit smaller values in terms of the information criteria and higher *adj*R^2. Most importantly they produce less mean square and absolute forecasting error (i.e., MSE and MAE). As before, we present the exact same picture with respect to the superior predictive power of the stability adjusted indexes in explaining 'future' banks' profits in both 'during-crisis' (*see Panel B*) and 'post-crisis' (*see Panel C*) periods by using estimated values of 2006 and of 2009 respectively. Overall adding leverage into the profit efficiency indicator increases the predictive power of the model for either additional indicator of risk that we use: that is, non-performing loans or variance of profits. A comparison among the two risk and stability adjusted profit

TABLE 12 Predictive power—Failed during the crisis (2007–2009).

lnROE	Credit risk Coefficient (standard error)	Credit risk with leverage Coefficient (standard error)	Variance of profits Coefficient (standard error)	Variance of profits with leverage Coefficient (standard error)
Pre-crisis—2006 versus 2003				
PE_2003	2.647***	3.692***	1.541***	1.927***
	(0.098)	(0.015)	(0.052)	(0.038)
F-stat	256.346	515.711	192.155	482.616
adjR^2	0.786	0.889	0.724	0.818
AIC	−5945.465	−8681.141	−5483.656	−8163.641
MSE	1.954	0.864	2.615	1.514
MAE	1.489	0.625	1.952	1.105
Observations	582	582	582	582

Note: This table presents results for the ordinary least squares (OLS) regressions for those banks that became insolvent during the financial crisis period (i.e., 2007–2009) where the dependent variable ROE (i.e., return on equity) is a proxy for bank profitability and one of the regressors (to shorten the size of the table we do not report the results of the parameters of the translog profit function—they are available upon request) is the profit efficiency level, in time 't-3', derived by four alternative risk-adjusted profit efficiency indexes, that is, a. credit risk, b. credit risk and leverage, c. variance of profits, d. variance of profits and leverage. The predictive power of the model is captured by the two conventional forecasting measurement errors, that is, the 'MSE' and MAE', that stand for the 'Mean Square Error' and the 'Mean Absolutely Error' respectively. Robust standard errors adjusted for bank clustering are reported. *, ** and *** denote significance at 10%, 5% and 1% level, respectively.

efficiency indicators reveals that the index that accounts for both an *ex-post* and a long run *ex-ante* indicator of risk (i.e., credit risk and leverage) is a better predictor of future profits than the one that includes the two *ex-ante* risk indicators or risk (i.e., variance of profit and leverage). In order to examine the statistical significance of our results, we performed a pairwise Diebold and Mariano (1995) test on each pair combination of models, for all three different time periods, to determine whether the forecast produced by each profit efficiency index does actually provide insights that are accurate and unique. The null hypothesis states that the models under consideration have the same predictive accuracy. Table 9 indicates that in most cases we are able to ascertain that the forecasts contained different information. Overall, in all three distinct time periods and for both forecasting errors, the model that includes a profit efficiency indicator that accounts for stability issues, is superior in terms of its forecasting power and shows that leverage is an important predictor of a bank's profit. The results are stronger in the pre-crisis and in the aftermath of the crisis period.[10] This confirms our suggested hypothesis stating that the inclusion of leverage in the estimation of profit efficiency increases both the indicator's explanatory and predictive power.

Moreover, to gain a more conclusive picture regarding the predictive ability of the four profit efficiency indexes as to which is superior, in addition to the Diebold and Mariano (1995) framework presented before, we test the model forecasts with the Model Confidence Set (MCS) procedure developed by Hansen et al. (2011). The procedure will sequentially test a null hypothesis of Equal Predictive Ability (EPA) for a matrix of forecast losses, tested at 0.01% confidence, dropping the worst model until the EPA is accepted as part of the Superior Set of Models (SSM). The results in Table 10 show that for all the states in the economy and for both forecasting errors (i.e., MSE, MAE) the profit efficiency indicators that include leverage are always included in the SSM. Specifically, the index that accounts for both a short run and a long run ex-ante indicators of risk is always ranked first for both the MSE and the MAE (in the 'pre-crisis'). On the contrary, the profit efficiency indicators that do not consider leverage are ruled out from the SSM for both forecasting errors in the 'during-crisis' period, while in the aftermath of the crisis period, the profit efficiency index that includes the variance of profits, is not included in the SSM as far as the MAE is concerned. Unequivocally, in all the periods around the crisis and for both forecasting errors, the indexes without leverage are always ranked in the two bottom places, which further strengthen our belief that leverage increases the profit efficiency indicator's predictive power.

6.2.1 | Conditional specification

Table 11 sheds light on the predictive power of all the profit efficiency indexes with regards to the banks that

TABLE 13 Predictive power—Failed after the crisis (2010–2012).

lnROE	Credit risk Coefficient (standard error)	Credit risk with leverage Coefficient (standard error)	Variance of profits Coefficient (standard error)	Variance of profits with leverage Coefficient (standard error)
Panel A: Pre-crisis—2006 versus 2003				
PE_2003	1.854***	1.653***	1.127***	1.261***
	(0.018)	(0.072)	(0.038)	(0.068)
F-stat	91.345	184.649	72.548	129.428
adjR^2	0.657	0.821	0.509	0.716
AIC	−2671.721	−3918.059	−1429.617	−3432.448
MSE	1.408	0.617	1.862	1.071
MAE	0.918	0.267	1.307	0.682
Observations	434	434	434	434
Panel B: During crisis—2009 versus 2006				
PE_2006	1.342***	0.815***	0.684**	0.715***
	(0.084)	(0.043)	(0.073)	(0.046)
F-stat	34.654	81.186	24.462	59.162
adjR^2	0.429	0.721	0.382	0.438
AIC	−3928.242	−6818.439	−2614.571	−4982.429
MSE	2.346	0.821	2.187	1.205
MAE	1.167	0.423	1.608	0.816
Observations	434	434	434	434

Note: This table presents results for the ordinary least squares (OLS) regressions for those banks that became insolvent in the aftermath of the financial crisis period (i.e., 2010–2012) where the dependent variable ROE (i.e., return on equity) is a proxy for bank profitability and one of the regressors (to shorten the size of the table we do not report the results of the parameters of the translog profit function—they are available upon request) is the profit efficiency level, in time 't-3', derived by four alternative risk-adjusted profit efficiency indexes, that is, a. credit risk, b. credit risk and leverage, c. variance of profits, d. variance of profits and leverage. Panel A and B refer to the 'pre-crisis' and 'during-crisis' period respectively. The predictive power of the model is captured by the two conventional forecasting measurement errors, that is, the 'MSE' and 'MAE', that stand for the 'Mean Square Error' and the 'Mean Absolutely Error' respectively. 'Robust standard errors adjusted for bank clustering are reported. *, ** and *** denote significance at 10%, 5% and 1% level, respectively.

managed to confront the detrimental effect of the last financial turmoil. To be more precise, we explore the forecasting power of the indexes by using the estimated profit efficiency levels in 2003, 2006, 2009 to explain the level of banks' profits in 2006 (Panel A), 2009 (Panel B) in 2012 (Panel C), respectively.

Unequivocally, in all these three forecasting scenarios, the results indicate that all indexes are significant from a statistical perspective. Nevertheless, the model that includes the (*ex-post*) risk and stability adjusted index, reports in all cases smaller forecasting error (for both MSE and MAE), smaller values in the information criterion (i.e., AIC) and higher values of $adjR^2$ and F-statistic. The model that includes the (*ex-ante*) risk and stability adjusted profit efficiency indicator is ranked second against all the aforementioned measures, followed by the two models that include indexes that do not take into account the leverage position of the banks.

Tables 12 and 13 convey the empirical evidence of the predictability power of the four profit efficiency measures regarding those banks that became insolvent either in the 'during-crisis' (2007–2009) or the 'post-crisis' (2010–2012) period. Specifically, in Table 12 we examine the forecasting power of all indexes by using the estimated profit efficiency levels first in 2003 to explain the level of banks' rents in 2006 of the institutions that went bankrupt during the 2007–2009 period. In Table 13 we report the predictive power of all the indexes by using the estimated profit efficiency scores in 2003 and in 2006 with respect to the level of banks' rents in 2006 (Panel A) and 2009 (Panel B) for the banks that failed in the aftermath of the financial turmoil. We found that all three scenarios mirrored the case of the 'saved' banks. Specifically, the models that have as an explanatory variable, the level of the estimated profit efficiency scores (that derived from the two suggested in this paper, risk and stability adjusted profit efficiency indexes) produce a smaller forecasting error, a smaller information criterion value and a better fit of data, compared to the models that incorporate as

TABLE 14 Explanatory power.

lnROA	Credit risk Coefficient (standard error)	Credit risk with leverage Coefficient (standard error)	Variance of profits Coefficient (standard error)	Variance of profits with leverage Coefficient (standard error)
Panel A: Pre-crisis—2003				
PE_2003	3.918***	4.646***	1.816***	2.048***
	(0.061)	(0.026)	(0.047)	(0.016)
F-stat	426.143	647.125	317.151	514.153
adjR^2	0.652	0.717	0.536	0.692
AIC	−7314.621	−9314.641	−6324.159	−8262.168
Observations	3076	3076	3076	3076
Panel B: Pre-crisis—2006				
PE_2006	1.816***	1.319***	1.628***	1.251***
	(0.032)	(0.049)	(0.061)	(0.018)
F-stat	215.147	462.961	341.758	428.494
adjR^2	0.529	0.627	0.421	0.572
AIC	−6926.908	−8816.128	−5612.415	−7681.452
Observations	3076	3076	3076	3076
Panel C: During crisis—2009				
PE_2009	1.902***	2.173***	1.726***	1.819***
	(0.031)	(0.058)	(0.015)	(0.071)
F-stat	354.641	518.154	395.154	483.517
adjR^2	0.589	0.692	0.483	0.618
AIC	−5715.152	−7048.417	−4906.468	−6904.582
Observations	3076	3076	3076	3076
Panel D: Post-crisis—2012				
PE_2012	1.816***	1.817***	1.577***	1.672***
	(0.047)	(0.039)	(0.019)	(0.072)
F-stat	286.497	468.188	227.649	398.189
adjR^2	0.74	0.854	0.698	0.787
AIC	−6921.649	−8159.123	−5197.584	−7165.143
Observations	3076	3076	3076	3076

Note: This table presents results for the ordinary least squares (OLS) regressions where the dependent variable ROA (i.e., return on assets) is a proxy for bank profitability and one of the regressors (to shorten the size of the table we do not report the results of the parameters of the translog profit function—they are available upon request) is the profit efficiency level derived by four alternative risk-adjusted profit efficiency indexes, that is, a. credit risk, b. credit risk and leverage, c. variance of profits, d. variance of profits and leverage. Panels A and B refer to the 'pre-crisis', whereas Panels C and D refer to the 'during crisis' and 'post-crisis' period, respectively. Robust standard errors adjusted for bank clustering are reported in parentheses. *, ** and *** denote significance at 10%, 5% and 1% level respectively.

one of their explanatory variables the estimates of the two conventional profit efficiency indexes.[11]

6.3 | Robustness checks

In order to test the precision of our empirical findings we conducted various robustness tests.

First, we considered a different measure of profitability, the Return on Assets (ROA) as a proxy of our dependent variable. Tables 14 and 15 show the results for all periods around the crisis for the explanatory and predictive power respectively. They suggest that the models that include the stability adjusted index, exhibit in all cases smaller values in the information criterion (i.e., AIC), higher values of $adjR^2$ and F-statistic and smaller mean

TABLE 15 Predictive power.

lnROA	Credit risk Coefficient (standard error)	Credit risk with leverage Coefficient (standard error)	Variance of profits Coefficient (standard error)	Variance of profits with leverage Coefficient (standard error)
Panel A: Pre-crisis—2006 versus 2003				
PE_2003	1.816***	2.088***	0.928***	1.159***
	(0.091)	(0.059)	(0.081)	(0.038)
F-stat	352.408	628.261	348.291	478.067
adjR^2	0.552	0.736	0.476	0.626
AIC	−4265.166	−7156.39	−3198.189	−5364.415
MSE	2.118	0.613	2.095	0.715
MAE	1.006	0.381	1.215	0.626
Observations	3076	3076	3076	3076
Panel B: During crisis—2009 versus 2006				
PE_2006	1.819***	1.673***	1.218***	1.348***
	(0.027)	(0.037)	(0.048)	(0.083)
F-stat	282.352	519.267	243.298	361.533
adjR^2	0.407	0.516	0.391	0.418
AIC	−3913.168	−6726.842	−2568.058	−4819.592
MSE	2.421	1.059	2.315	1.152
MAE	1.539	0.726	1.927	1.064
Observations	3076	3076	3076	3076
Panel C: Post-crisis—2012 versus 2009				
PE_2009	0.529***	0.656***	0.716***	0.795***
	(0.018)	(0.091)	(0.014)	(0.067)
F-stat	305.256	581.551	292.257	418.656
adjR^2	0.513	0.689	0.413	0.593
AIC	−4034.941	−6916.428	−2846.331	−5103.527
MSE	2.205	0.816	2.155	0.923
MAE	1.148	0.463	1.431	0.706
Observations	3076	3076	3076	3076

Note: This table presents results for the ordinary least squares (OLS) regressions where the dependent variable ROA (i.e., return on assets) is a proxy for bank profitability and one of the regressors (to shorten the size of the table we do not report the results of the parameters of the translog profit function—they are available upon request) is the profit efficiency level, in time 't-3', derived by four alternative risk-adjusted profit efficiency indexes, that is, a. credit risk, b. credit risk and leverage, c. variance of profits, d. variance of profits and leverage. Panel A, B and C, refers to the 'pre-crisis', 'during crisis' and 'post-crisis' period, respectively. The predictive power of the model is captured by the two conventional forecasting measurement errors, that is, the 'MSE' and 'MAE', that stand for the 'Mean Square Error' and the 'Mean Absolutely Error' respectively. Robust standard errors adjusted for bank clustering are reported in parentheses. *, ** and *** denote significance at 10%, 5% and 1% level respectively.

square and absolute forecasting error (i.e., MSE and MAE) as far as the forecasting power is concerned.

Secondly, we test the robustness of results with regards to the bank size. Prior banking research has been inconclusive with regards to relations between bank size and efficiency.

Some studies propose that large banks generate higher levels of profit efficiency than small banks (Manlagnit, 2011; Tecles & Tabak, 2010), while others show that small banks are more profit-efficient than large banks (e.g., Mamatzakis et al., 2008). To account for the fact that effects of efficiency may be different for small banks (GTA ≤81 billion) and large banks (GTA >1 billion), we reran our analyses for these two bank size classes in all the states of the economy, for both their explanatory and predictive. Results suggest that our main findings hold for both classes of bank size, but that the size of the coefficients are generally higher for the large banks, although the statistical significance is generally greater for small banks, likely due to the much larger numbers of observations. Thirdly, we take into account the too-big-to-fail doctrine. Our concern is that the results may be driven by the very large banks considered too-big-to-fail (TBTF), and more likely to be bailed out in the event of problems. To mitigate any effects in this regard, we repeat the last steps of our empirical strategy while excluding these banks. There is no formal definition of TBTF, so we use the Dodd-Frank Act definition of by deeming that all banks with gross total assets (GTA) of at least 850 billion[12] constitute systematically important financial institutions (SIFIs). Once again, the findings are not significantly different to our main results, suggesting that our inferences are not driven by the TBTF banks.[13] Overall, the results support the view that leverage is an important indicator of bank risk and stability when estimating banking efficiency.

7 | CONCLUDING REMARKS

In this study we shed light on the impact of leverage on efficiency by considering an indicator of profit efficiency which takes into account the trade-off that bank managers face between efficiency and stability. This relies on the role of leverage as an indicator of a bank's stability. We test the superiority of this indicator by comparing both its explanatory and predictive power of future profits with alternative bank efficient indicators, including different measures of risk. We also compare the robustness of our risk and stability adjusted index and the conventional ones in the literature, in terms of the ordering of the banks according to their profit efficiency scores, in three different states of the economy.

Results show that profit efficiency indicators that include leverage are better predictors of future profits than those that include other indicators of risk. Moreover, the efficiency indicator that accounts for both an *ex-post* (i.e., credit risk) and a long run *ex-ante* (i.e., leverage) indicator of risk, outperforms all other efficiency indicators used currently in the literature. Specifically, it shows the least deviation in the ordering of banks with respect to their efficiency scores. Furthermore, the model that includes the risk (*ex-post*) and stability (leverage) adjusted profit efficiency index has smaller values in the information criterion metric (AIC), higher value in the fitness of data metric (adjR^2) and higher value regarding the overall significance of the model metric (F-stat). This highlights its superiority in terms of its explanatory power. In addition, the smaller values that are produced in two different forecasting errors, signify the superiority of the index as far as its predictive power is concerned. Our findings remain qualitatively unaffected against a wide battery of robustness tests.

Our conclusions are relevant from a policy perspective in light of the recently implemented leverage ratio under the Basel III regulatory framework. Although banking leverage played an important role as a determinant in the last financial crash, the theoretical literature that analyses the effect of introducing a non-risk-based leverage ratio alongside a risk-based capital framework provides mixed results on whether it decreases risk-taking (Barth & Seckinger, 2018; Blum, 2008; Hugonnier & Morellec, 2017; Kiema & Jokivuolle, 2014). Thus, our study provides important new insights with policy implications on the determination of the optimal leverage ratio via the profit efficiency channel. Moreover, given the importance of bank efficiency to economic growth and to the wider economic environment (Berger et al., 2004; Gaganis et al., 2021; Hasan et al., 2009), bank supervisors, social planners and regulators, should consider closely monitoring of the joint optimal level of efficiency and stability generated through timely use of our proposed efficiency indicator so as to reduce the occurrence of problems during future financial crises and extreme market disruptions, such as natural disasters and the COVID-19 pandemic as well as the current energy crisis. Given the on-going economic uncertainty, these ideas can be used as a basis for future research.

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CONFLICT OF INTEREST STATEMENT

The author has no conflicts of interest to disclose.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID

Konstantinos N. Baltas https://orcid.org/0000-0002-5665-2871

ENDNOTES

[1] Hughes and Mester (2008) pointed out that this measure of inefficiency fails to consider whether a bank's managers are assuming either too much or too little risk relative to the value-maximizing amount.

[2] The selection of both the dependent and independent variables is consistent with several other studies in the literature, (e.g., Berger & Mester, 1997; Delis et al., 2014; Lozano-Vivas & Pasiouras, 2010).

[3] A Markov transition matrix derives from a Markov chain which is a mathematical system that undergoes transitions from one state to another on a state space.

[4] For the sake of euphony 'half-tile' refers to a two-by-two Markov transition matrix.

[5] We consider the profit efficiency indicator that accounts for both credit risk and leverage as our preferred one as it takes into account not only the level of risk employed by the bank manager's actions, but also the long run implication of his decisions regarding the bank's stability as well.

[6] We perform a simple Chow (1960) test for a structural break at the beginning (i.e., in 2007) and in the end (i.e., in 2009) of the financial crisis and find strong evidence of a structural change in both points in time. In particular, the Chow test rejects the null hypothesis of no break (or constant parameter values), thereby providing evidence that the difference in the subperiods regressions is statistically significant. Other studies, like that of Cornett et al. (2011)—also use 2007 and 2009 as the starting and ending points of the crisis respectively.

[7] Our results are robust when we alternatively winsorize at 2.5% and 97.5% levels and at 1% and 99% levels.

[8] We also conduct a bootstrap analysis for the parameters' significance tests to examine whether our empirical evidence is driven by any outliers. The results remained unchanged after performing a different number of resampling iterations.

[9] For convenience, we present only the results of the predicted profits in 2006, 2009, 2012 as a function of profit efficiency indicators 3 years earlier. However, for the other years we get similar qualitative results (the outcomes are available upon request).

[10] As in the case of the explanatory power, we bootstrap the p-values for the parameters' significance tests with regards to the predictive power. Subject to a different volume of resampling iterations the empirical evidence does not change.

[11] As before, we conduct a pairwise Diebold and Mariano (1995) test on each pair combination of models, as well as we test the predictive power of the profit efficiency indicators via the MSC methodology, for both solvent and insolvent (in both different periods) institutions as far as the global financial crisis is concerned. The empirical evidence of both exercises highlights the important role that leverage play in predicting a bank[3]s profit in all three different states of the economy. The results are available upon request.

[12] There are not enough observations to analyse the TBTF banks by themselves.

[13] The results for all three different categories of banks, that is, large, small and TBTF are available upon request.

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