Shareholder Value Efficiency: Methods and Evidence from the US Banking Industry

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Abstract

We propose generalized frontier analysis (GFA), a simple and computationally efficient method for estimating economic frontiers. While previous research assumes that the production function under which firms operate is either parametric or deterministic in nature, we apply the theory of asymmetric loss functions in combination with a nonparametric and stochastic estimation method to relax these potentially restrictive assumptions. We use GFA to estimate shareholder value efficiency of US banks on a large sample of 118,164 bank-year observations for the period 1994-2010. Using a broad set of criteria, we find that GFA provides valid efficiency scores, which are economically and statistically more meaningful in explaining value creation of US banks than both managerial ability and conventional efficiency scores. We also demonstrate the generality of GFA by investigating other economic frontiers such as cost efficiency. Overall, our analysis indicates that GFA is an attractive method for modeling economic measures of efficiency.

JEL Classification: C45, G21, G28, E58

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1. Introduction

Economic measures of efficiency, such as cost efficiency, provide information on the extent to which banks and their managers are able to choose inputs efficiently so as to minimize the cost of producing a given output bundle relative to the industry technology. Analogously, the related concepts of revenue and profit efficiency describe similar phenomena. The literature has focused on efficiency measures because these allow comparisons between economic entities using varying input and output bundles. From the perspective of shareholders, however, these economic quantities may not always accurately align with their objective functions, since these stakeholders are primarily motivated by value creation. It is likely that cost, revenue or even profit efficiency, albeit necessary, are not sufficient conditions for value to be created efficiently.

Fiordelisi (2007) has formulated the concept of shareholder value efficiency (SHVE), which may be efficacious in mitigating these issues. However, the SHVE concept has previously been operationalized by stochastic frontier analysis (SFA), which is not without limitations. Hence we contribute to the discussion in four ways. First, we develop a novel method for efficiency measurement (generalized frontier analysis, GFA) that overcomes the limitations of the more traditional approaches. Second, we apply our method to shareholder value efficiency and compare its performance with stochastic frontier analysis across a broad set of criteria. We thus provide an important check on the plausibility of the shareholder value efficiency concept. Further, shareholder value efficiency has so far only been studied in the European context. Hence our third contribution is to provide the first evidence on the shareholder value efficiency of US banks. Fourth, our study is the first to establish a link between value creation and managerial ability for banks. Our sample covers virtually the entire population of US commercial banks and contains 118,164 bank-year observations during the years 1994 through 2010.

Banks face an essential trade-off between risk taking and value creation. Shareholder value efficiency has been linked to value creation (Fiordelisi and Molyneux, 2010). Furthermore, banks

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1 As an example consider the case where excessive cost saving efforts negatively impact the ability of a bank to screen loans, such that the ensuing losses exceed the initial cost savings. Further misalignment between conventional efficiency and value creation may be due to other factors such as agency problems (see Berger and Bonaccorsi di Patti, 2006; Hughes, Lang, Mester, Moon and Pagano, 2003; Jensen and Meckling, 1976).
that underperform in terms of value creation have been found to be more risky (Cipollini and Fiordelisi, 2012). These findings suggest that shareholder value efficiency might be an important concept that can capture these significant dimensions of bank behavior. The shareholder value efficiency metric indicates how well a bank’s management chooses its input and output mix so as to optimize value creation relative to the latent transformation function spanned by its industry peers. Shareholders aim for value maximization within the bounds imposed by technology and competition. Therefore this measure likely aligns better with their objective functions than conventional efficiency measures. However, if banks faced homogenous economic, regulatory and competitive conditions and if in addition managers’ and owners’ interests were fully aligned, managerial ability should be a better indicator of bank value creation than SHVE because in this setting more able managers would automatically run more valuable banks. In this case, managerial ability would be a better indicator of bank value creation than SHVE and the SHVE concept would be redundant. The presence of these idealized conditions is always a question of degree and is at the same time difficult to estimate directly. Therefore, it is important to investigate the information content of SHVE vis-à-vis managerial ability when it comes to explaining value creation in US banks. We carry out this as yet extant validation exercise in the present research.

The received parametrization of SHVE relies on stochastic frontier analysis to generate a frontier that explains value creation, as proxied by economic value added (EVA), by way of a Translog production function parametrized in terms of input quantities and output prices. The use of SFA to parametrize shareholder value efficiency raises three main concerns, however. First, only one method (SFA) for the parametrization of the shareholder value efficiency measure is available. However, since efficiency is a latent concept, having an alternative parametrization method would provide decision makers with a valuable plausibility-check of SHVE scores. The need for such a check is highlighted by findings in the efficiency literature, which show that alternative

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Data Envelopment Analysis (DEA), the natural alternative, can unfortunately not be used in the case of shareholder value efficiency. This is because economic frontiers based on DEA would require the computation of optimal shareholder value creation from the optimal, feasible input and output mix given prices. Such an approach is straightforward in the case of, for example, cost efficiency, but it is less obvious which “prices” could link input and output quantities to shareholder value (see for example, Coelli, Rao, O’Donnell and Battese, 2005).
Parametrizations of efficiency may provide widely different results (Bauer, Berger, Ferrier and Humphrey, 1998; Huang and Wang, 2002). Second, SFA postulates that the functional form linking input and output information to the economic quantity of interest is known and that firm inefficiency follows a known distribution. These assumptions may be justified in cases such as cost efficiency, where the applied researcher has a concrete theory available for guidance. However, no such theory is available for shareholder value creation. To the contrary, highly nonlinear patterns of value creation may result from, for example, increased tail risk due to adverse effects of earnings management (Andreou, Cooper, Louca and Philip, 2013; Balboa, López-Espinosa and Rubia, 2013) or opacity (Morgan, 2002). These complexities substantially reduce the likelihood that a priori parametric assumptions regarding the production function will adequately capture the underlying process.

Third, SFA requires a rigid classification of assets and liabilities as either inputs or outputs. However, this will ignore synergies between different asset classes as well as the dual role of certain assets, such as derivatives, that can be used by banks as both inputs and outputs. Our proposed method overcomes these restrictive assumptions.

Ideally, an efficiency parametrization method will have three main properties. First, it should have the capacity to find an envelope for the data that provides plausible efficiency scores that are robust to noise. Second, it should not require prior knowledge or restrictive assumptions about the data generating process. Third, it should be able to parametrize various efficiency measures, both economic and technical. In general, such a method will consist of two components: an estimation component, whose task is to fit a production function, and a component ensuring that what is estimated is in fact a frontier and not merely an average production function.

Hence we develop a simple and computationally efficient method (GFA) that satisfies all of the above criteria. We adopt a nonparametric approach to operationalize the estimation component. Specifically, we use artificial neural networks, which have been shown to have the capacity to approximate both functions and their quantiles arbitrarily well (Hornik, Stinchcombe and White, 1989; White, 1992). To operationalize the frontier component we rely on Granger’s (1969) asym-

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3Even in the cases for which theoretical underpinnings do exist, the incompatibility of commonly assumed production functions, such as the Translog, with reality has been noted particularly for the banking sector (see e.g. Mitchell and Onvural, 1996).
metric loss functions, which have been applied for example in the field of forecasting (Christoffersen and Diebold, 1997). We note that instead of using artificial neural networks, any other non-linear approximator such as kernel regression could have been used as the estimation component. This would however require that a compatible frontier component can be devised. Thus our GFA method is generalized in two senses. First, it does not require restrictive assumptions regarding the form of the transformation function and the distribution underlying the error terms. Second, it can be used to fit not only shareholder value efficiency but also other measures of economic and technical efficiency. We demonstrate this capability by applying GFA to cost efficiency.

Our main results are as follows. In the descriptive domain, we examine the statistical properties of shareholder value efficiency as well as the univariate relations between SHVE and typical bank performance indicators that do not rely on frontier concepts. We find that GFA and SFA provide similar efficiency scores, which shows that GFA is a viable efficiency parametrization method. However, we also find that GFA shareholder value efficiency scores tend to provide more information on the performance of US banks than do SFA scores. In the inferential domain, we use a multivariate setting to examine the economic and statistical significance of shareholder value efficiency both vis-à-vis managerial ability and cost and revenue efficiency. We find that SHVE is more informative with respect to value creation than both managerial ability and other efficiency scores. This underscores the importance of the SHVE concept. We also show that the SFA and GFA efficiency scores contribute to the explanation of shareholder value creation independently of one another, which confirms that they capture similar but not identical information. However, more importantly, GFA is found to provide SHVE scores that are both economically and statistically more meaningful in explaining value creation than the comparable SFA-based scores. Finally, we demonstrate the generality of the GFA method by also investigating cost efficiency. We find support for the greater information content of this method in comparison to both stochastic frontier analysis and data envelopment analysis. Thus, overall, these results vindicate the GFA method and validate the shareholder value efficiency concept.

The remainder of this paper is organized as follows: Section 2 presents our proposed method; Section 3 discusses the data; Section 4 presents our empirical results, including robustness checks
and additional analysis; and Section 5 concludes.

2. The Generalized Frontier Analysis Method

In this section we introduce the GFA method in two steps. First, we discuss the estimation component; and second, the frontier component. The estimation component consists of a standard artificial neural network as visualized in Figure 1. Here, simple units (neurons) are marked as circles and organized in layers. Each neuron takes the sum of all incoming connections and applies a smooth nonlinear function to this sum. The light grey neurons on the left correspond to the feature vector, which provides information about bank inputs and outputs. The central unit marked with “+1” is a so-called “bias-unit” and can be thought of analogously to the constant in conventional regression, in the sense that it always outputs a value of unity. The intermediate neurons mark the hidden layer, while the dark grey, right-hand neuron represents the output layer. Here the neural network provides a prediction about the shareholder value of a given bank. All layers in the net are fully connected to the immediately preceding and immediately subsequent layers by a set of weights. These weights are the free parameters that are set by way of standard optimization procedures such as gradient-descent.

More formally, let the weight matrices \( \mathbf{\Theta}^{(l)} \) and bias vectors \( \mathbf{\beta}^{(l)} \) represent the free parameters of the GFA structure. Each neuron in layer \( l \) cumulates the input from all previous neurons in layer \( l - 1 \), to obtain the input signal

\[
\mathbf{z}^{(l)} = \mathbf{\Theta}^{(l-1)} \mathbf{a}^{(l-1)} + \mathbf{\beta}^{(l-1)}
\]

and applies the sigmoid transfer function

\[
g = \frac{1}{1 + \exp(-x)}
\]

This resulting quantity is referred to as the activation of the nodes in layer \( l \), \( \mathbf{a}^{(l)} = g(\mathbf{z}^{(l)}) \). This procedure is repeated for all \( L \) layers. In the following we will be using a neural net with a single hidden layer with 10 nodes and no recurrent connections.

\[\text{[Figure 1 about here.]}\]

4There are other choices available in the literature such as the hyperbolic tangent function. Generally the choice of transfer function is found to have relatively little effect on results (Haykin, 1999). Since the partial derivatives of this function plateau for output values going toward 0 and toward 1, we scale our target data to the interval [0,1,0,9] (see also Balakrishnan and Honavar, 1992 and Athanassopoulos and Curram, 1996).

5This is a relatively sparse parametrization. Given 10 nodes in the first and second layers and 1 node in the final layer, we have \( 11 \times 10 + 10 = 120 \) free parameters. Compare this with the “rule of thumb” of Mitchell and
We define \( a^{(L)} = h_{\Theta^{(1)}, \Theta^{(2)}, \beta^{(1)}}(x) \), the output of the final layer, as the hypothesis that the system generates about the desired target value \( y \) when the associated feature vector is provided as input \( x \). \( h \) is also computed using the sigmoid transfer function \( g \) defined above.

To optimize the parameters, some sort of loss function will need to be minimized. A standard approach in the literature is the sum of squared errors \( (SE(\Theta^{(1)}, \Theta^{(2)}, \beta^{(1)}, x, y) = \frac{1}{2} \| (h_{\Theta^{(1)}, \Theta^{(2)}, \beta^{(1)}}(x) - y) \|^2 \) (Haykin, 1999). Using an optimization procedure, to adjust the weights of this system so as to fit the data, would return an approximation to average production technology. However, we want to fit a frontier, not an average production function. To overcome this challenge we introduce the “frontier” component of the GFA algorithm.

The mechanism that ensures the fitting of a frontier in the context of GFA hinges on the concept of asymmetric loss functions. Arguably first investigated by Granger (1969), this type of function involves differential treatment of prediction errors across various parts of the domain. It has been utilized for example by Christoffersen and Diebold (1997). Typically an asymmetric loss function consists of two linear branches starting at the origin, whose slopes differ in the positive and negative directions (consider for example, Crone (2002) for an application to neural nets for forecasting). We are the first to apply this approach in the efficiency context. In lieu of the aforementioned squared error function \( (SE) \), we can write the asymmetric loss function, \( QQ \), as:

\[
QQ(\Theta^{(1)}, \Theta^{(2)}, \beta^{(1)}, a, b, x, y) = \begin{cases} 
\frac{a}{2} \| (h_{\Theta^{(1)}, \Theta^{(2)}, \beta^{(1)}}(x) - y) \|^2 & \text{if } y > h_{\Theta^{(1)}, \Theta^{(2)}, \beta^{(1)}}(x) \\
0 & \text{if } y = h_{\Theta^{(1)}, \Theta^{(2)}, \beta^{(1)}}(x) \\
\frac{b}{2} \| (h_{\Theta^{(1)}, \Theta^{(2)}, \beta^{(1)}}(x) - y) \|^2 & \text{if } y < h_{\Theta^{(1)}, \Theta^{(2)}, \beta^{(1)}}(x).
\end{cases}
\]

(1)

Here the asymmetry is determined by the factors \( a \) and \( b \). In our specific case we wish to consider a shareholder value frontier. Banks that are more shareholder value efficient will exhibit greater levels of shareholder value for given levels of inputs and outputs. Therefore the frontier is approaching shareholder value from above. Thus we do not interpret as an error the prediction of

Onvural (1996) who recommend Number of Observations\(^{2/3}\) orthogonal series terms in the implementation of the flexible fourier form. In our case for 2010, the year with the smallest number of observations, this would amount to 314 coefficients for the orthogonal series terms alone. Unsurprisingly, Feng and Serletis (2009) find prohibitively expensive computational cost in the context of their constrained FFF method.
lower shareholder value than that actually observed. Rather, this merely implies that the bank has been inefficient compared to other banks with a similar input-output-mix. However, observing a bank that has a level of shareholder value above the predicted level would mean that this bank has been super-efficient. Since the frontier should envelop the sample of banks, we treat this case as a prediction error to be penalized. We accomplish this by setting \( a > b \). The GFA will then predict the locally maximum level of shareholder value that is feasible. We define shareholder value efficiency as the ratio of actual shareholder value and maximum feasible shareholder value:

\[
SHVE = \frac{y}{h_{\Theta^{(1)}, \Theta^{(2)}, \beta^{(1)}}(x)}
\]

The specification is stochastic because the neural net separates signal from noise, and is nonparametric because it requires no assumptions regarding functional form or error distribution. In the following we report results with \( a = 1000 \). Consequently, if we consider all \( m \) observations in our sample, the loss function can be written as:

\[
C(\Theta^{(1)}, \Theta^{(2)}, \beta^{(1)}, a, b, x, y, \lambda) = \frac{1}{m} \sum_{i=1}^{m} QQ(\Theta^{(1)}, \Theta^{(2)}, \beta^{(1)}, a, b, x^i, y^i) + \frac{\lambda}{2} \sum_{l=1}^{L} \sum_{i=1}^{s_l} \sum_{j=1}^{s_{l+1}} (\Theta^{(l)}_{ji})^2.
\]

Here we add a regularization term (akin in spirit to ridge regression) with a weight of \( \lambda \) to avoid uncontrolled parameter growth and minimize the risk of overfitting the data (Gnecco and Sanguineti, 2009). We set this term to 0.5.

In the next step we aim to minimize this loss function by adapting the free parameters in \( \Theta^{(1)}, \Theta^{(2)} \) and \( \beta^{(1)} \). This is done iteratively by way of a gradient descent method, which is commonly referred to as backpropagation (see for example, Werbos, 1974; Haykin, 1999). Particularly

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6 Results depend to a certain extent on the magnitude of the asymmetry parameters \( a \) and \( b \). As default we set \( b = 1 \). We experimented with values of \( a \in [10; 10^2; 10^3; 10^4] \) in our initial grid search. The ability of the neural net to recognize the patterns in the data suffered for greater values of \( b \), particularly for \( b \geq 10^5 \). Results are robust for lower values of \( b \); thus, in order to not favor our method unduly, we select a fairly large asymmetry parameter.

7 To analyze the sensitivity of results with respect to a number of parameter choices, we use different values for the number of units in the intermediate layer and for the weight decay parameter. Our results are robust to various choices of the number of hidden units and the weight decay parameter so that we do not see the need to optimize the values for these parameters explicitly in designing our neural net. Concretely, we conducted a preliminary grid search over variations with \([5; 10; 20; 100]\) hidden units and weight decay parameter values of \( \lambda \in [0; 0.1; 0.5; 1; 10] \). Weight decay of 10 detracted from prediction accuracy slightly; otherwise results were robust to different parameter choices. Adding an extra hidden layer with 5 hidden units neither contributed nor detracted from the quality of our results. The net was initialized with the Nguyen and Widrow (1990) initialization algorithm and we found results to be robust to initial conditions. We trained the net for a maximum of 100 iterations of full batch gradient descent.
for each weight, connecting node $j$ in layer $l+1$ and node $i$ in layer $l$, we modify the corresponding weight as follows ($\mu$ is the rate of adaptation for each step):

$$\Theta^{(l)}_{ji} = \Theta^{(l)}_{ji} - \mu \frac{\partial C(\Theta^{(1)}, \Theta^{(2)}, \beta, a, b, x, y, \lambda)}{\partial \Theta^{(l)}_{ji}}.$$  \hfill (3)

Similarly, for the bias weights:

$$\beta^{(l)}_{j} = \beta^{(l)}_{j} - \mu \frac{\partial C(\Theta^{(1)}, \Theta^{(2)}, \beta, a, b, x, y, \lambda)}{\partial \beta^{(l)}_{j}}.$$  \hfill (4)

In order to be able to compute the partials ($\partial$), we calculate the hypothesis of the net for each input vector $x$ by using this as an input to the first layer and passing it through the network. Then the partial derivative of the weights in the final layer with respect to the error produced by the hypothesis is given by:

$$\delta^{(L)} = \begin{cases} 
  a(a^{(L)} - y) \cdot g'(z^{(L)}) & \text{if } y > a^{(L)} \\
  0 & \text{if } y = a^{(L)} \\
  b(a^{(L)} - y) \cdot g'(z^{(L)}) & \text{if } y < a^{(L)}.
\end{cases}$$  \hfill (5)

This value is then used in the computation of the gradients ($\nabla$) of the loss function with respect to each weight. Because $g'(x) = g(x)(1 - g(x))$, it can be shown that the “local gradients” (Haykin, 1999) at layer $l$ can be written as $\delta^{(l)} = (\Theta^{(l)})^T \delta^{(l+1)} \cdot (a^{(l)} \cdot (e - a^{(l)}))$, where the operator $\cdot$ denotes the product of each element of the first matrix with only the corresponding element of the second (Hadamard product) and $e$ is a vector of ones. This computation is carried out for all layers but the first. The desired partials are then given by:

$$\nabla C_{\Theta^{(l)}}(\Theta^{(1)}, \Theta^{(2)}, \beta, a, b, x, y, \lambda) = \delta^{(l+1)}(a^{l})^T$$  \hfill (6)

and

$$\nabla C_{\beta(l)}(\Theta^{(1)}, \Theta^{(2)}, \beta, a, b, x, y, \lambda) = \delta^{(l+1)}.$$  \hfill (7)

These results are then used to update the weights of the incidence matrices by way of gradient descent. We show the full algorithm in Appendix A.2.

The approach using asymmetric loss functions is new to the literature dealing with the application of flexible functional forms to the estimation of efficiency. The seminal work on the use of artificial neural networks in the context of efficiency is attributable to Athanassopoulos and Curram [1996]. The authors devise a neural net that will fit an average production function to the data. They then avail themselves of a shifting procedure to obtain a “frontier” from this average prediction. Concretely they define efficiency as the quotient between observed and predicted values and they generate the frontier by adding to each predicted output value the maximum prediction error over all samples. They refer to this concept as a “normalized frontier” since efficiency scores are less than unity. However, this method uses an ad hoc correction to the estimates. Our approach on the other hand can do away with this ad hoc manipulation and estimate a frontier from the data directly.

A recent extension of the literature is provided by Michaelides, Vouldis and Tsionas [2010], who investigate distance functions parametrized by way of neural nets. Their research aims to use neural nets for the parametrization of the reduced form equations included in the distance function system. Thus they use the neural net to parametrize the production technology but resort to the conventional estimation via seemingly unrelated regressions along with attendant assumptions. Our approach differs substantially from theirs in that we wish to obtain the efficiency estimates directly from the generalized frontier analysis. We use it as a standalone, one-step method akin to SFA rather than incorporating neural concepts within other statistical approaches. Since SFA is relatively well known given its long-standing history in the literature, we confine the discussion of this method to the Appendix A.1.
3. Data and Variables

We adopt the intermediation approach proposed by Sealey and Lindley (1977) in order to define inputs and outputs and in so doing place our research in line with many prior studies.\footnote{\textit{e.g.} Bauer, Berger, Ferrier and Humphrey (1998), Berger (2003). Surveys such as Fethi and Pasiouras (2010) confirm that the majority of studies overall adopt this approach.} We follow Berger (2003) in selecting as inputs labor (number of full-time-equivalent employees), purchased funds, core deposits, physical capital and equity. We treat physical capital and equity as fixed inputs since these are not freely disposable in the short run. As outputs, we define consumer loans, business loans, real estate loans, securities and off-balance-sheet items. We treat the last output category as fixed, as there is no obvious flow definition that would allow a straightforward calculation of the corresponding price. Prices are computed following the localized approach of Berger and Bonaccorsi di Patti (2006), where, using information from the Summary of Deposits database, we localize banks into markets according to metropolitan statistical areas and non-metropolitan statistical area counties. Otherwise all our data related to firm-level efficiency stems from the December Call reports for 1994-2010, available from the Chicago branch of the Federal Reserve. All variables are adjusted to 2005 US dollars using the GDP implied deflator. Banks with less than USD 10 million gross total assets are eliminated from the sample (Berger and Bouwman, 2009). We also eliminate observations with equity/asset ratios of less than 1% or greater than 100%. We likewise delete observations with return on equity greater than 1 or less than -1. We note that the timespan we are studying includes at least two periods of considerable turmoil in financial markets, the collapse of the “dot-com bubble” of 2000-2001 and the financial crisis of 2007-2009. One of our aims is to analyze the validity of efficiency parametrization methods as well as the degree to which they agree or disagree. In that respect the presence of periods exhibiting high levels of noise is a welcome test of the methods under study as regards their ability to deal with such noisy data. We therefore deal with the periods in question only insofar as we refrain from using panel data methods or pooled data for the estimation of efficiency. Rather we estimate efficiency over yearly data and thus allow each efficiency parametrization method to adjust the shape of its prediction to the respective prevailing economic climate. This also ensures
compatibility of the SFA and GFA results, since there are as yet no panel extensions for GFA available.

Our empirical analysis sets out to accomplish two main objectives. First, we want to investigate whether the proposed GFA method is able to provide a meaningful indicator of shareholder value efficiency and whether that indicator is compatible with efficiency scores derived from SFA. Second, we want to understand the information content of this method in terms of explaining shareholder value creation in US banks. Hence we proceed in two steps.

Since efficiency is a latent concept, the validity of efficiency scores can only be investigated indirectly. Therefore we build on Bauer, Berger, Ferrier and Humphrey (1998) in order to investigate the first objective. These authors provide a comprehensive set of consistency criteria that can be used to investigate whether different efficiency parametrizations provide plausible conclusions about the underlying technology. They propose to investigate the similarity between efficiency scores obtained from different methods along both the statistical and economic dimensions. The aim of the statistical analysis is to investigate whether the various efficiency scores have similar distributional properties, whether they provide similar rankings of banks and whether they identify similar groups of banks as particularly efficient or inefficient. The validation analysis aims to assess the degree to which efficiency scores align with the stylized facts of the banking industry, and how plausibly they associate with typical nonfrontier measures of performance. While Bauer, Berger, Ferrier and Humphrey (1998) include only return, revenue and cost characteristics among these measures, we expand the set of nonfrontier performance criteria to encompass the CAMELS rating criteria as completely as possible. This mnemonic represents Capital adequacy, Asset structure, Managerial ability, Earnings, Liquidity and Sensitivity. Specifically, we include return on assets (ROA) to proxy for managerial ability (Beatty and Liao, 2011) and economic value added (EVA) to proxy for the earnings dimension. We include the equity over asset ratio to proxy for the capital adequacy dimension, liquid assets over total assets to capture liquidity, and nonperforming loans over total loans to capture asset structure. We do not investigate sensitivity explicitly.

In deriving our measure of shareholder value creation, we follow Fiordelisi (2007).
So far, the bulk of the analysis is based on rank correlations, following Bauer, Berger, Ferrier and Humphrey (1998). However, correlations, rank or otherwise, may be unstable. Therefore, in our second step, we additionally investigate the information content of the two shareholder value efficiency parametrizations, using regression analysis. Specifically, we analyze the information content of the shareholder value efficiency scores with respect to one another and vis-à-vis other efficiency scores and common control variables. This analysis enables us to gain insight into the value creation process in US banks.

4. Empirical Results

In this section we report our main empirical results. Specifically, we offer results on the statistical and economic analyses of Bauer, Berger, Ferrier and Humphrey (1998) in Sections 4.1 and 4.2. We report the results of our regression analyses in Section 4.3.

4.1. Statistical Analysis

We turn first to the analysis of statistical properties of the two shareholder value efficiency scores. These results are reported in Table 1.

|Table 1 about here.|

To interpret the results we use as our benchmark the study of Fiordelisi (2007), which reports values around 60% for shareholder value efficiency for European banks. Given that the orientation toward maximizing shareholder value is generally thought to be more stringently implemented in the US, it is not entirely surprising to obtain values of around 65% for the same timespan. Overall we find an average SHVE of 75% from the GFA parametrization (Panel A), while SFA indicates an average SHVE of around 70%. Although a direct comparison between efficiency scores of European and American banks is not possible, this does show that on average US banks are closer to their efficient frontier than are their European counterparts. This also resonates with Hughes, Lang, Mester, Moon and Pagano (2003), who find that listed US banks are approximately 80% market
value efficient. Market value efficiency requires the bank to be listed. However the majority of US banks is private, which makes SHVE an important indicator of value creation efficiency. As expected, the nonparametric frontier obtained from generalized frontier analysis yields somewhat greater efficiency scores. Only GFA can account naturally for negative shareholder value efficiency. This will occur in a constellation when a firm is predicted to create positive value but in fact ends up destroying value. SFA cannot accommodate this feature and requires data manipulation to achieve nonnegative values of shareholder value prior to fitting the frontier (see A.1). This is another conceptual advantage of GFA over SFA. We also note that the GFA method provides lower variation in efficiency scores and both methods plausibly report negative skewness of efficiency scores. The greater dispersion and difference between mean and median for the SFA method suggests that this method may be providing some outlying efficiency scores. While these tests reveal that differences between SFA and GFA exist, the literature has documented far greater differences between parametric and nonparametric methods such as SFA and DEA (Huang and Wang, 2002; Bauer, Berger, Ferrier and Humphrey, 1998). Therefore SFA and GFA can be treated as methods providing compatible efficiency scores. In Panel B we investigate the (rank) correlations between the efficiency scores. If the efficiency parametrization methods are reasonably compatible, we should expect a positive similarity between the efficiency scores respective to the efficiency-based rankings of banks. Our two methods provide strong and highly significant positive rank correlations, which indicates that the two methods provide compatible efficiency parametrizations. This impression is further strengthened by considering the overlap between the best and worst practitioners in the US banking industry. The rationale behind considering the overlap between the best and worst performing firms is that even if two efficiency score distributions do not align well in their totality, they can still be efficacious, for example in terms of policy implications, if they identify similar firms as being highly (in-)efficient. We therefore investigate (in Panel C of Table 1) the fraction of firms that any pair of methods simultaneously places in the best (worst) percentiles of banks. Concretely, we identify those banks that are located in the top or bottom 1st, 5th, 10th and 25th percentile of the efficiency distribution and compare the proportion of firms that overlap between any two efficiency parametrization methods.
We then use a $\chi^2$ test to check whether statistically the overlap is significantly different from our expectation of overlap due to chance. We compute the overlap for quantile $Q$ subsets of two sets $A, B$ with $M$ and $N$ elements as follows:

$$O = \frac{C(A_Q \cap B_Q)}{\min(M, N)},$$

where $C$ signifies the cardinality. We find that statistically overlaps are significantly greater than chance, which further strengthens our conclusion that the GFA and SFA methods provide compatible results. This shows that GFA is a suitable efficiency estimation method that produces valid results.

### 4.2. Validation Analysis

Having established that the shareholder value efficiency scores obtained from SFA and GFA share many statistical properties, we investigate whether the resulting efficiency scores also align with the stylized facts of the US banking industry. Hence we analyze the association between efficiency scores and nonfrontier indicators of performance. Such indicators represent various facets of bank performance and we choose these indicators so as to cover the CAMELS regulatory rating criteria as completely as possible.

Shareholder value efficiency indicates how close a given bank is to choosing an input-output mix that would enable it to create the maximum technically feasible shareholder value. We therefore expect banks with higher SHVE to be more profitable (have a higher ROA) and to generate lower (higher) levels of cost (revenue) for a given level of value created. We also expect that higher SHVE should be positively associated with economic value added (our measure of value creation). We split this variable into its two components, economic profits (EP) and the capital charge. We would further expect that more shareholder value efficient banks will align positively with greater economic profits and lower capital charge. More efficient banks have been shown to possess better loan selection and monitoring skills (Chortareas, Girardone and Ventouri, 2011). Hence we expect more SHVE banks to have lower levels of nonperforming loans. Where the
capitalization of banks is concerned, there are two possible expectations: either greater efficiency can reduce equity in the expectation that future profits will offset this initial shortage (see for example, the efficiency-risk hypothesis of Altunbas and Chakravarty (2001)); alternatively, more shareholder value efficient banks will aim to protect their valuable charter by reducing risk and thus holding greater amounts of equity (see for example, the franchise value hypothesis of Berger and Bonaccorsi di Patti (2006)). A similar argument can be constructed for the fraction of liquid assets over total assets. Hence we do not formulate explicit expectations for these two variables.

It has been shown that the production technology of banks may differ by size, for example due to economies of scale or relationship lending (Berger, Miller, Petersen, Rajan and Stein, 2005). Hence we carry out the validation analysis for the full sample as well as for subsamples split by banks’ size. Specifically, we rerun the parametrization of the shareholder value efficiency frontier for each subsample and investigate the respective correlations for each subsample separately. We split the sample at the 50th and 90th percentiles to account for the strong asymmetry in bank size across the US banking industry (Feng and Serletis, 2009). We report our findings in Table 2.

![Table 2 about here.]

We now turn to a discussion of our full sample results, reported in Panel A. In particular, we find that both methods provide efficiency scores that align well with nonfrontier bank characteristics for the full sample. Thus the efficiency scores capture the majority of the expected relationships. Specifically, more shareholder value efficient banks are more profitable ($ROA$), have lower cost ($\frac{Total\ Cost}{Total\ Assets}$) and greater revenue ($\frac{Total\ Revenue}{Total\ Assets}$), higher shareholder value creation ($\frac{EVA}{Total\ Assets}$) and a better quality loan portfolio ($\frac{Nonperf.\ Loans}{Total\ Loans}$). These banks produce both greater economic profits ($\frac{EP}{Total\ Assets}$) and lower capital charges ($\frac{Capital\ Charge}{Total\ Assets}$). The SFA and GFA methods disagree on the association between shareholder value efficiency and capitalization ($\frac{Equity}{Total\ Assets}$). While SFA associates more shareholder value efficient banks with less equity and fewer liquid assets ($\frac{Liquid\ Assets}{Total\ Assets}$), the GFA efficiency scores predict the opposite relationship. Both explanations are plausible given the findings in the literature. Concretely, it appears that the GFA efficiency scores are capturing the benefits gained from risk aversion and preservation of a valuable bank charter,
while the SFA scores reflect a more aggressive banking strategy. More importantly, however, the
two methods agree on a majority of the relationships. This further strengthens the conclusion that
the GFA and SFA methods are generally compatible, albeit with distinct information content.

Next, we discuss the results for the split sample analysis (Panels B-D). Here, we estimate a
separate frontier for each subsample of banks based on the conjecture that size might be driving
significant technological differences between banks. We find that across subsamples and methods,
more SHVE banks are more profitable, have lower cost and greater revenue per unit assets, and
produce greater economic profits and EVA. They also generate a lower capital charge, although for
medium and large banks only GFA is significant here. They further appear to hold less risky loan
portfolios; again for large banks only GFA is significant. Furthermore, more SHVE banks seem to
reduce equity holdings (only GFA is significant for small and medium banks). While small banks
appear to favor liquid assets, medium banks slightly reduce this balance sheet position. Again
this is indicated only by GFA.

Overall, the validation analysis reveals that both SFA and GFA shareholder value efficiency
scores are associated in plausible ways with other nonfrontier measures of bank performance.
More shareholder value efficient banks appear to accomplish this efficiency by a strong focus on
loan portfolio quality and profitability. Both cost minimization and revenue maximization are
beneficial for value creation in these banks. These findings are largely independent of bank size.
We also find that, probably due to the greater flexibility of the GFA method, the efficiency scores
derived from this parametrization are more informative than those derived from SFA, judging by
the greater frequency of significant rank correlations.

4.3. Regression Analysis

We investigate the explanatory contribution and economic relevance of shareholder value efficiency
to the analysis of value creation in US banks. To this end we formulate the following baseline
model:

\[
\frac{EVA_{i,t}}{C_{i,t-1}} = \alpha + \beta \psi - \text{eff}_{SFA,i,t} + \gamma \psi - \text{eff}_{GFA,i,t} + \xi' z_{i,t} + \sum_{t=1}^{17} \theta_t d_t + v_i + \epsilon_{i,t}.
\]  \(9\)

Here \(\psi - \text{eff}_{m,i,t}\) is shareholder value efficiency estimated by the method \(m\) for \(m \in \{SFA, GFA\}\). \(d_t\) are time dummies, \(v\) is a firm fixed effect and \(\epsilon\) is the disturbance. Standard errors are clustered by banks. In further specifications we add \(x - \text{eff}_{m,i,t}\) cost efficiency and \(\tau - \text{eff}_{m,i,t}\) revenue efficiency. We also investigate the importance of managerial ability (\(MA\)) for bank value creation. In so doing we follow the method of Demerjian, Lev and McVay (2012). We also add control variables (\(z\)), which include \(ROA\), the log of gross total assets (\(BKSIZE\)), the ratio of nonperforming loans to total loans (\(NPL\)) and the leverage (\(LEV\)) of the bank. As our dependent variable we use economic value added scaled by lagged capital invested, to reflect the flow nature of value creation. The use of lagged capital invested reduces our sample to 106,564 bank-year observations.

Our results are reported in Table 3. In our various specifications we explore the explanatory contribution of SHVE estimated by GFA and SFA. The specific questions are threefold. First, we ask whether the SHVE scores of one method subsume the information conveyed by the SHVE scores estimated by the other method (Specifications 1-6). Second, we also examine whether SHVE contains additional information above and beyond that included in cost and revenue efficiency (Specifications 7-10). Finally, we investigate whether the information of SHVE might be subsumed by managerial ability, in Specifications 11 and 12. In so doing we are not only able to address a question of economic relevance but also simultaneously mitigate endogeneity concerns arising from omitted variable problems. We tested the above fixed effect models against the random effects model using the Hausman (1978) test and found that the random effects approach is overwhelmingly rejected in our data. We therefore choose the fixed effects model. In the following regressions, we obtain SHVE estimates by splitting the sample of banks by size at the 50th and

\[11\] Multicollinearity of regressors is not problematic in our dataset. Thus the greatest correlation of around 0.6 occurs between the cost and revenue efficiency measures (CE and RE) and their lags. These lags are included into unreported regressions without qualitatively affecting the main results (full results available on request).
90th percentiles. We estimate a separate frontier for each subsample and then pool the resulting efficiency scores. Coefficient estimates and significances are qualitatively unaffected if we instead estimate the frontier over the full sample of banks. We standardize all regressors to z-scores in all models. This will enable us to understand the economic significance of this measure. In addition to these regressions, we also investigate the contribution that the efficiency scores make to the explanation of value creation in Table 3.

We first analyze the information content of the SHVE measures one vis-à-vis the other in Specifications 1-6. Consider first Specifications 1 and 3. Here we compare the economic significance of SHVE parametrized by SFA and GFA respectively. First, we note that the economic importance of GFA is superior to that of SFA. Thus, the impact of a one standard deviation change in the GFA-SHVE score amounts to a change in value creation of 3.83% of capital invested, while the equivalent effect is only 2.97% for SFA. Given that the average bank creates value on the order of 5.37% of capital invested, a 3.83 percentage point increase is substantial. Although less extreme, the greater economic importance of GFA-SHVE holds when control variables are added to the regression in Specifications 2 and 4. Furthermore, between Specifications 1 and 3, we note that the GFA specification exhibits a substantially greater adjusted $R^2$. From the control variables we find that more value-creating banks are more profitable ($ROA$), more highly leveraged ($LEVRAG$) and larger ($BKSIZE$). Moreover, we find that these banks have a weak preference for higher quality loan portfolios ($NPL$). These results align with our findings from the validation analysis. In Specifications 5 and 6 we include SFA and GFA-SHVE jointly, both with and without control variables. GFA-SHVE is again more economically significant in both cases. Specifically, when GFA and SFA are jointly included in the regression, the t-statistic for the SFA-SHVE nearly halves and the coefficient decreases from 0.0297 to 0.0211 vis-à-vis Specification 1. On the other hand, the decrease in the GFA coefficient is only from 0.0383 to 0.0337, with the t-statistic virtually unchanged. Even so, we note that including both SHVE measures provides a significant increase of the adjusted $R^2$ which, along with the fact that both SHVE parametrizations maintain
their significance, confirms our finding from the validation analysis that the two SHVE measures contain similar but distinct information sets, with GFA being the more informative measure.

Next, we turn to the analysis of the Specifications 7-10. Here we investigate whether SHVE makes a meaningful contribution to the explanation of value creation above and beyond the contribution of cost and revenue efficiency. In economic terms, we examine whether being cost or revenue efficient is a sufficient condition for value creation. We find from all four specifications that cost efficiency tends to have a negative impact on value creation, while revenue efficiency is weakly positive. This is regardless of whether cost and revenue efficiency are parametrized using SFA or GFA.\footnote{This documents the ability of GFA to measure efficiency scores other than SHVE. We explore cost efficiency scores derived from GFA vis-à-vis SFA and DEA at length in additional analysis. In further unreported analysis (available upon request) we rerun Specifications 9 and 10 using SFA to parametrize cost and revenue efficiency, with qualitatively unchanged results.} A reasonable explanation for this finding could run as follows. Cost efficiency gains are likely to require restructuring initiatives that inevitably cause frictions and may destroy value, at least initially. Consider for example initial organizational difficulties after staff have been laid off. The organizational adjustments inevitably cause a loss of value at the outset, while the leaner structure may be beneficial in the long run.\footnote{We find support for this explanation by including lags of cost efficiency in unreported specifications, again results available on request. The lags are found to be positively significant for value creation.} Unsurprisingly, revenue efficiency is positive as it likely entails an expansion of economic activity and may for example subsume beneficial scale effects. Again we find that the economic significance of the GFA-SHVE scores is greater than that of the SFA scores. We also observe that the inclusion of cost and revenue efficiency into the regression provides only a marginal increase in adjusted $R^2$, which suggests that SHVE is an important driver, while cost and revenue efficiency cannot be viewed as sufficient for value creation.

A main source of doubt about the validity of regression analyses is the potential for endogeneity. Specifically, it is conceivable that both shareholder value creation and shareholder value efficiency are highly correlated with an unobserved third factor, the influence of which has not been filtered out by the other control variables in the regression.\footnote{Alternatively, reverse causation might be influencing results if being more shareholder value efficient entails greater value creation and greater value creation can lead to higher shareholder value efficiency. However, this source of endogeneity is not as troubling in our context as we do not aim at establishing causation.} A prime candidate for such an omitted
factor would be managerial ability \((MA)\). Hence we include a proxy of managerial ability in our Specifications 11 and 12. The ability of management to influence the performance of firms has been shown to be substantial \cite{beatty2011management, bertrand2003statistical}. Demerjian, Lev and McVay \cite{demerjian2012management} argue that a key function of management is to maximize revenue in an efficient manner. However the revenue efficiency of a bank will depend on more than just the activities of management. Therefore, one should purge revenue efficiency scores of bank-specific effects and use the resulting residual as the indicator of managerial ability. The authors use data envelopment analysis (DEA) to obtain revenue efficiency scores and purge these of bank-specific effects by Tobit-regressing them on a set of controls.\footnote{Cantrell \cite{cantrell2013empire} has shown that this measure is an efficacious indicator of managerial ability in banks.} Therefore we compute this measure of managerial ability and include it in our regression specifications.

In addition to making our inference more robust to the influence of endogeneity, this approach will allow us to learn more about the importance of bank managers for value creation. That is, we examine whether SHVE is an important driver of value creation or whether its impact is fully subsumed by the ability of management. On the one hand, one could argue that it is a central task of managers to maximize the creation of value on the behalf of owners. Thus we should expect managerial ability to be positively related to value creation. However, managerial ability \((MA)\) may not be an adequate indicator of value creation. Factors facilitating this case include asymmetric effects of local market heterogeneity on banks and their managers, or adverse effects such as empire building, agency problems or earnings management, which have been sufficiently documented in the literature \cite{jensen1976theory, hughes2003empire, shen2005empire}. In this case we expect SHVE to retain its significance and sign, and to contribute more to the explanation of value creation than managerial ability.

In Specification 11 we find that, as expected, managerial ability is positively and highly significantly associated with value creation. Its impact, however, is not as economically significant, judging by the magnitude of the coefficients relative to those of the SHVE scores. This shows that SHVE scores are important in explaining the creation of value in US banks in their own right. Furthermore, this points to the existence of some of the problems mentioned above. We leave dis-

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\footnote{Cantrell \cite{cantrell2013empire} has shown that this measure is an efficacious indicator of managerial ability in banks.}
entangling the precise reasons for this finding to future research as a thoroughgoing investigation of this question is beyond the scope of this paper. Furthermore, we find that endogeneity arising from omitted variables is not driving our main results. Both the SFA- and GFA-based SHVE scores maintain the signs and significances that were observed in the main analysis. Finally, it has been argued in the literature (Beatty and Liao, 2011) that ROA can proxy for managerial ability. To alleviate the concern that this effect may be driving the low economic significance of MA in Specification 11, we rerun the regression while excluding ROA in Specification 12. While the coefficient on MA does increase somewhat, it is still far smaller than that of the SHVE measures, which supports our initial interpretation.

Table 4 about here.

The final step of our regression analysis focuses on the explanatory contribution of the SHVE measures, vis-à-vis one another and vis-à-vis cost and revenue efficiency as well as managerial ability. It could be that even though less economically significant, SFA-SHVE is a statistically more informative variable in explaining value creation. To explore this question, we re-estimate each of the models above various times. On each run we omit one efficiency score. We record the change in adjusted $R^2$ resulting from adding a particular efficiency score and tabulate the percentage change in adjusted $R^2$ in Table 4. The column headers identify the Specification that is being considered.

Given that these regressions include fixed time and firm effects, the contributions to adjusted $R^2$ made by the shareholder value efficiency scores are substantial. Thus, including SHVE parametrized by GFA into a model that has only fixed effects contributes 28.1% to adjusted $R^2$ (Specification 3). The comparable contribution of SFA is lower, but still a sizeable 16.5%. Control variables mute the explanatory contribution of the SHVE scores but cannot eliminate it, as is shown in Specifications 2 and 4. In all cases, the GFA-SHVE scores are more informative than those obtained from SFA. This is supported by specification 5, in which we include both SHVE measures. Here GFA-SHVE contributes 19.3% to the adjusted $R^2$, while the SFA counterpart only delivers 6.3%. Interestingly, the contribution to the explanation of value creation provided
by cost and revenue efficiency is vanishingly small (Specifications 7-10). Although slightly greater contributions of the GFA cost efficiency scores suggest that the greater information content for the GFA efficiency scores might hold not only for SHVE but also for cost and revenue efficiency scores, we do not overemphasize this result. Finally, in Specification 11 we find that managerial ability, is almost irrelevant to explaining value creation. This is in line with our findings from the preceding analysis, where MA is found to be economically only marginally significant. This finding holds even when ROA is excluded from the regression (Specification 12). As before, GFA is the more meaningful out of the two SHVE variables in these two Specifications (11, 12).

In sum, we conduct a number of analyses which establish that GFA is a suitable method for the estimation of efficiency scores. We show that it is both more economically significant and more informative in this respect than equivalent efficiency scores obtained from SFA. We further demonstrate that SHVE is an important concept that cannot be simply subsumed under cost and revenue efficiency or managerial ability.

4.4. Robustness Checks

In order to ensure that our analysis is providing valid and reliable results, we carry out a number of (unreported) robustness checks. First, to check that the SHVE scores themselves are not spurious, we calculate the correlation of the efficiency scores in period $t$ and all periods $t + 1$ until $T$. We expect to observe positive correlations that decrease over time, since efficiency is likely to be a bank characteristic that changes only slowly. We find precisely this pattern for both SFA and GFA.

Second, as regards the validation analysis discussed in Section 4.2, we rerun the analysis for a balanced sample of banks. We find qualitatively unchanged results. We also rerun the analysis for nonfrontier performance measures shifted one period into the future; in other words we examine the capacity of SHVE scores to predict nonfrontier performance characteristics of banks. We find that both SFA and GFA provide meaningful and plausible predictions. We also investigate the relationship between SHVE and nonfrontier performance multiple periods into the future and find
that the dynamic patterns displayed by the rank correlations of nonfrontier performance indicators both with the SFA- and GFA-SHVE measures are remarkably similar. We further consider the correlation of the long-sectional average of SHVE scores with the long-sectional average of bank nonfrontier characteristics. Again we find highly significant and plausible correlations for both SFA and GFA.

Third, the main analysis uses the standard definition of managerial ability proposed by De-merjian, Lev and McVay [2012]. In order to assure the robustness of our results, we modify this definition by using a yearly specification for $MA$ instead of a pooled cross-sectional one. We also change the set of control variables used in the first-stage regressions to purge the revenue efficiency scores from bank-specific factors. Our results hold. Furthermore, we re-estimate the specifications in Table 3, including lags of the efficiency scores and of managerial ability, because one might argue that efficiency takes time to influence value creation. We find qualitatively unchanged results. All of these results are available upon request.

4.5. Generalized Frontier Analysis for Cost Efficiency

Results thus far indicate that GFA accurately captures the SHVE scores. In this section we investigate the ability of GFA to estimate other types of firm-level efficiency. Hence, we carry out a series of plausibility checks for cost efficiency and compare not only SFA and GFA but also DEA scores. We choose cost efficiency because it is a common benchmark in the efficiency measurement literature (Fethi and Pasiouras, [2010]) and because this choice allows us to compare results with the findings of Bauer, Berger, Ferrier and Humphrey [1998]. In addition, this enables us to compare our GFA method with the DEA approach. DEA is nonparametric but deterministic, GFA, on the other hand, is both nonparametric and stochastic, thus comparing these two methods yields further valuable insight into the performance of GFA. Reported in Table 5 are only the results of the validation analysis, to conserve space.

[Table 5 about here.]

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16 Conducting this type of analysis for revenue and profit efficiency yields qualitatively similar results. 17 The full set of results is reported in the Online Appendix and is also available upon request.
Since cost efficiency captures a different dimension of bank behavior than shareholder value efficiency, we naturally have different expectations about the likely associations between cost efficiency scores and nonfrontier indicators of bank performance. Specifically, if a bank engages in aggressive cost reduction efforts in order to become more cost-efficient, the motive will usually be profit maximization. Hence we expect a positive association with return on assets (ROA).

On average, we would expect that the component of EVA that relates to the cost of capital will be lower for more cost-efficient banks, assuming that they extend their cost saving efforts to capital budgeting decisions. Hence we expect a negative association between cost efficiency and \( \frac{\text{Cap. Charge}}{\text{Total Assets}} \). Similarly, provided cost saving initiatives are successful, economic profits should be positively associated with cost efficiency. Hence we expect a positive correlation between cost efficiency and \( \frac{\text{EP}}{\text{Total Assets}} \). Note however that, because of the univariate nature of the analysis, this does not necessarily imply that more cost-efficient banks are more value-creating; observing the expected signs on economic profits and capital charge does not guarantee that banks are both efficient managers of capital and strong generators of economic profits, both of which would be necessary for value creation. In addition, less tangible adverse effects of cost saving initiatives can include demotivation of staff, less thorough management of market risk etc. (Fiordelisi and Molyneux, 2010). Hence the association between cost efficiency and value creation (\( \frac{\text{EVA}}{\text{Total Assets}} \)) is difficult to anticipate. The focus on risk management also influences the amount of liquid assets held. While these assets are costly in an opportunity cost sense, they ensure low bank risk. Hence our expectation is equally ambiguous for \( \frac{\text{Liquid Assets}}{\text{Total Assets}} \). Intuitively, more cost-efficient banks should have lower overall cost so that we expect correlations between cost efficiency and \( \frac{\text{Total Cost}}{\text{Total Assets}} \) to be negative. However, the influence on revenue is not so clear. Thus cost reduction initiatives may well lead to a decrease in the overall volume of operations (downsizing) that is more than offset by a decrease in revenue, for example because of branch closures that may lead to loss of market share. However, a leaner organizational structure, induced by greater cost efficiency, may well lead to a greater revenue generation relative to the asset base of the bank. Hence the coefficient on \( \frac{\text{Total Revenue}}{\text{Total Assets}} \) is difficult to pin down ex ante. The same holds for equity over total assets. Whether a more cost-efficient structure entails a reduction of risk and thus a
reduction of borrowing costs or a tighter financing structure and hence lower cost of capital is
difficult to predict. The “Efficiency-Risk Hypothesis” posits that a more efficient bank, in the
expectation of higher future returns, will maintain a lower capital base (Berger and Bonaccorsi
di Patti, 2006). However, part of the related “Efficient Structure Hypothesis” predicts that more
efficient banks will persistently generate higher profits, which may be driving higher equity ratios
(see for example Berger, 1995, Mester, 1996 and Casu and Girardone, 2006). Both hypotheses
are plausible and the literature has not reached a consensus. Hence conflicting predictions as to
the association between cost efficiency and \( \frac{Equity}{Total\ Assets} \) are the result. Finally, the cost to banks
from nonperforming loans can be substantial. Anticipating this, we expect that banks will steer
their cost efficiency initiatives in such a way as to ensure a high quality loan portfolio. This is
equivalent to the “Efficiency Lending Quality Hypothesis” of Chortareas, Girardone and Ventouri
(2011). Therefore we expect a negative sign on \( \frac{Nonp.\ Loans}{Total\ Loans} \).

We find that banks that are highly ranked on cost efficiency also tend to be highly ranked in
terms of return on assets (\( ROA \)). This holds both for all banks and across all subsamples. However,
only GFA is consistently able to provide a significant correlation. Similarly straightforward
is the finding that more cost-efficient banks have lower levels of cost (\( \frac{Total\ Cost}{Total\ Assets} \)), which is robust
across methods and subsamples as well. GFA and DEA are likewise in agreement in terms of the
association between cost efficiency revenue as a fraction of assets, while SFA is uninformative in
this respect (\( \frac{Total\ Revenue}{Total\ Assets} \)). Specifically, the coefficient indicates that more cost-efficient banks
will also be more revenue generating, which suggests that our “lean organization” interpretation,
proposed above, appears more likely than the alternative “downsizing” explanation. While SFA
and GFA suggest that across all banks holding more equity is positively associated with cost effi-
ciency, thus emphasizing the risk motive, DEA suggests the opposite, that is, stresses the cost of
capital motive (\( \frac{Equity}{Total\ Assets} \)). All methods agree, at least for the full sample of banks, that more
cost efficiency is on average detrimental for value creation (\( \frac{EVA}{Total\ Assets} \)). On the other hand, GFA
suggests that for small and medium sized banks, the opposite may be the case. SFA and DEA are
uninformative in this regard. All methods are in agreement that this observation may be due to a
lower economic profit (\( \frac{EP}{Total\ Assets} \)) that is partially offset by an equally lower (or higher in the case
of DEA) capital charge \(\frac{\text{Cap. Charge}}{\text{Total Assets}}\). Consistent with our expectation, small and medium banks hold lower levels of liquid assets to the extent that they are more cost-efficient \(\frac{\text{Liquid Assets}}{\text{Total Assets}}\). This is confirmed by GFA and DEA for the subsamples, while SFA is uninformative. It may be the case that the risk aversion motive is more pervasive for the full sample of banks since here SFA and GFA suggest a positive relation. Finally, all methods seem to agree that more cost-efficient banks are also better loan monitors, as expected \(\frac{\text{Nop. Loans}}{\text{Total Loans}}\). We observe some important changes in sign between the full sample of banks and the subsamples. This provides support for the conjecture that banks of different sizes are subject to somewhat different production functions as noted, for example in the economies of scale literature (see for example McAllister and McManus, 1993, Wheelock and Wilson, 2001; Berger, Miller, Petersen, Rajan and Stein, 2005; and Asaftei, 2008). Overall, GFA aligns well with both SFA and DEA, while more frequently providing significant information about bank performance, as in the shareholder value efficiency case.

5. Conclusion

We propose a novel method, generalized frontier analysis, for the estimation of economic and technological frontiers. This method is nonparametric and stochastic and hence combines the advantages of previous approaches without inheriting their limitations. We apply this method to the shareholder value efficiency of a large sample of US commercial banks. Our main analysis investigates the shareholder value creation of US banks and we also show the ability of GFA to compute other efficiency measures, specifically cost efficiency.

We find that both the SFA and the GFA methods provide efficiency scores that have plausible distributional characteristics. This validates GFA as an efficiency measurement approach. Furthermore, we observe that the efficiency scores from GFA align with other nonfrontier indicators of bank performance. In particular, we find relations between these nonfrontier performance measures and SHVE that conform with reasonable priors derived from the literature. More importantly however, when considering a sample split by bank size, we show that GFA provides efficiency scores that contain at least as much information about bank performance as equivalent
SFA-based scores. This further corroborates the capacity of GFA to parametrize efficient frontiers.

Moreover, SHVE scores derived from GFA have a greater economic impact on the value creation of US banks than similar scores derived from SFA. This also holds when managerial ability is included in the analysis, which implies that SHVE is an important driver of value creation in its own right and not simply a proxy for the ability of management. Managerial ability is in turn found to be a statistically significant but economically marginal driver of bank value creation. Furthermore, we find the economic and statistical significance of cost and revenue efficiency to be equally negligible compared to SHVE. This confirms that cost and revenue efficiency are not sufficient for the creation of value. These results are robust to a wide variety of robustness checks.

Our analysis confirms that shareholder value efficiency can be parametrized by way of GFA and that it is a meaningful concept that can make a contribution to our understanding of bank value creation. While we show that managerial ability is an important variable that influences value creation in banks, it would be of interest to investigate through which channels managerial ability is able to do so, why its impact is lower than that of SHVE and why it does not subsume the information in the SHVE scores completely.
A. Appendix

A.1. Stochastic frontier analysis

The use of stochastic frontiers in the analysis of firm efficiency traces its lineage to Aigner, Lovell and Schmidt (1977). Since then numerous studies have applied this method in various industries. Since the impact of different flavors of SFA, be it through choices of the functional form or through assumptions on the error term, are by now well known and generally found to be of relatively small importance where consistency is concerned (see Bauer, Berger, Ferrier and Humphrey, 1998; Huang and Wang, 2002), we confine our analysis to the standard normal-half normal cross sectional SFA model of Aigner, Lovell and Schmidt (1977). This model assumes that the total level of value creation can be described as follows:

\[ EVAi = s(y_i, w_i, \beta) \exp(\epsilon_i) \]  

(A.1)

Here \( y_i \) is the \( M \times 1 \) output bundle of bank \( i \) and \( s \) is the deterministic kernel of the shareholder value creation function. We choose a Translog specification with linear homogeneity in prices imposed (see equation A.2). \( w_i \) are the \( N \) input prices faced by the \( i \)th bank and \( EVAi \) is the total shareholder value generated by this producer which can be computed by way of \( w_i'x_i \) where \( x_i \) represents the \( N \times 1 \) input vector of the \( i \)th bank. \( \epsilon_i = v_i - u_i \) is the composed error term where \( v_i \) is assumed \( \sim iidN(0, \sigma^2_v) \) and represents the random influences of the environment the bank is subject to. The nonnegative inefficiencies of banks are represented by \( u_i \), which is assumed to be \( \sim iidN^+(0, \sigma^2_u) \). Both error components are assumed to be independent of each other and the regression parameters. To extract the firm level inefficiencies from the data we use the Battese and Coelli (1988) estimator. We generate estimates of all parameters using maximum likelihood, obtained through gradient-descent-based maximization of the log likelihood function.

To estimate firm-level shareholder value efficiency using SFA one must specify a deterministic kernel that represents the production technology. We employ the widely used Translog functional

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\(^{18}\text{Notation mostly follows Kumbhakar and Lovell (2003).}\)
form. This can be specified as follows:

\[
\ln(EVA_i + \phi) = \beta_0 + \sum_{m=1}^{M} \alpha_m \ln y_{mi} + \sum_{n=1}^{N} \beta_n \ln w_{ni} + \sum_{q=1}^{Q} \gamma_q \ln z_{qi} \\
+ \frac{1}{2} \sum_{m=1}^{M} \sum_{j=1}^{M} \alpha_{mj} \ln y_{mi} \ln y_{ji} + \frac{1}{2} \sum_{n=1}^{N} \sum_{k=1}^{N} \beta_{nk} \ln w_{ni} \ln w_{ki} \\
+ \frac{1}{2} \sum_{q=1}^{Q} \sum_{r=1}^{Q} \gamma_{qr} \ln z_{qi} \ln z_{ri} + \sum_{m=1}^{M} \sum_{n=1}^{N} \delta_{mn} \ln w_{ni} \ln y_{mi} \\
+ \sum_{m=1}^{M} \sum_{q=1}^{Q} \eta_{mq} \ln y_{mi} \ln z_{qi} + \sum_{q=1}^{Q} \sum_{n=1}^{N} \kappa_{qn} \ln w_{ni} \ln z_{qi} + u_i + v_i. \tag{A.2}
\]

Here \(y_{mi}\) represents the quantity of output \(m\) produced by bank \(i\), \(w_{ni}\) represents the price of the \(n^{th}\) input used by bank \(i\) and \(z_{qi}\) is the quantity of the \(q^{th}\) fixed input/output used by the \(i^{th}\) bank. \(\alpha, \beta, \gamma, \delta, \eta, \kappa\) are coefficients to be estimated. \(\phi\) is a coefficient added to each EVA realization to ensure nonnegative values before taking logs. This parametrization corresponds to the alternative profit efficiency approach of Berger and Mester (1997).

Linear homogeneity in prices requires:

\[
\sum_{n=1}^{N} \beta_n = 1, \quad \sum_{n=1}^{N} \beta_{nk} = 0 \quad \forall k, \quad \sum_{n=1}^{N} \delta_{nm} = 0 \quad \forall m \quad \text{and} \quad \sum_{n=1}^{N} \kappa_{nq} = 0 \quad \forall q. \tag{A.3}
\]

The usual symmetry conditions are \(\alpha_{mj} = \alpha_{jm}\), \(\beta_{nk} = \beta_{kn}\), \(\gamma_{qr} = \gamma_{rq}\).

**A.2. Generalized Frontier Analysis Algorithm**

Following from the discussion in Section 2 we let \(\Theta\) and \(\beta\) stand for all weight matrices and bias vectors when written without a superscript. We can then write the GFA training algorithm as:
Algorithm 1 Gradient Descent with Backpropagation Algorithm

Set $\Delta \Theta^{(l)} := 0 \land \Delta \beta^{(l)} := 0 \forall l$

for $i = 1 : m$ do
  $\triangleright$ Compute $\nabla C_{\Theta^{(l)}}(\Theta, \beta, a, b, x_i, y_i, \lambda)$ and $\nabla C_{\beta^{(l)}}(\Theta, \beta, a, b, x_i, y_i, \lambda)$
  \begin{align*}
  \text{for } l = L - 1 : 2 & \text{ do} \\
  \quad \triangleright \text{Compute } \delta^{(L)} \text{ as in equation 5} \\
  \quad \delta^{(l)} &= (\Theta^{(l)})^T \delta^{(l+1)} \bullet (a^{(l)} \bullet (e - a^{(l)})) \\
  \quad \nabla C_{\Theta^{(l)}}(\Theta, \beta, a, b, x_i, y_i, \lambda) &= \delta^{(l+1)}(a^{(l)})^T \\
  \quad \nabla C_{\beta^{(l)}}(\Theta, \beta, a, b, x_i, y_i, \lambda) &= \delta^{(l+1)} \\
  \text{end for}
  \\
  \text{Set } \Delta \Theta^{(l)} := \Delta \Theta^{(l)} + \nabla C_{\Theta^{(l)}}(\Theta, \beta, a, b, x_i, y_i, \lambda) \forall l \\
  \text{Set } \Delta \beta^{(l)} := \Delta \beta^{(l)} + \nabla C_{\beta^{(l)}}(\Theta, \beta, a, b, x_i, y_i, \lambda) \forall l
\end{align*}

end for

$\Theta^{(l)} = \Theta^{(l)} - \mu \left[ \left( \frac{1}{m} \Delta \Theta^{(l)} \right) + \lambda \Theta^{(l)} \right] \forall l \quad \triangleright \text{Update the parameters}$

$\beta^{(l)} = \beta^{(l)} - \mu \left( \frac{1}{m} \Delta \beta^{(l)} \right) \forall l$

References


Figure 1:
Possible Architecture of a GFA kernel with Four Input Units, Four Hidden Units and One Output Unit

Circles represent nodes, arrows represent weights connecting nodes. These are the free parameters of the network. The light grey nodes represent the input layer, the dark grey node represents the output layer. The remaining nodes represent the hidden layer and the bias unit (marked “+1”). Information is passed through the network from left to right.
Table 1: Statistical Analysis of Shareholder Value Efficiency Parametrization Methods. This table reports results relating to the statistical analysis. Panel A shows distributional properties computed on a yearly basis and then averaged across years. Stars indicate significance levels at 0.01 (**), 0.05 (**) and 0.1 (*) levels. Panel C reports the overlap between top and bottom percentiles of banks as classified by the two efficiency parametrization methods. * indicates significant difference from 25% (10%, 5%, 1%) at the 10% level (Chi-square test, two-tailed). SFA indicates stochastic frontier analysis. GFA indicates generalized frontier analysis (asymmetry parameter \( a = 1000 \)).

### Panel A: Distributional Properties

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<thead>
<tr>
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<th>GFA</th>
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<td>median</td>
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<tr>
<td>min</td>
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<tr>
<td>std</td>
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<td>skewness</td>
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### Panel B: Correlations

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<td>Kendall</td>
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### Panel C: Overlaps

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<td>0.4551*</td>
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<tr>
<td>0.3050*</td>
<td>0.5046*</td>
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<td>Top 5%</td>
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<tr>
<td>0.2703*</td>
<td>0.4884*</td>
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<td>Top 1%</td>
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</tr>
<tr>
<td>0.2849*</td>
<td>0.3292*</td>
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Table 2: Correlation of Bank Shareholder Value Efficiency with Nonfrontier Performance Measures.

This table reports Spearman rank correlations between different efficiency measures and nonfrontier indicators of performance for the population split by size into the smallest 50%, the medium 40% and the largest 10% of banks. Stars indicate significance levels at 0.01 (***) and 0.05 (**) and 0.1 (*) levels. SFA indicates stochastic frontier analysis. GFA indicates generalized frontier analysis (asymmetry parameter $a = 1000$). ROA represents return on assets, EP denotes economic profit, EVA denotes economic value added.

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<tr>
<th>Correlates</th>
<th>$E[\text{sgn}]$</th>
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<th>GFA</th>
<th>SFA</th>
<th>GFA</th>
<th>SFA</th>
<th>GFA</th>
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<th>GFA</th>
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<tr>
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<td>All Banks</td>
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<td>Medium Banks (50-90%)</td>
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<tr>
<td>ROA</td>
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<td></td>
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<tr>
<td>Total Cost</td>
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<tr>
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<td>-0.1153**</td>
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<td>-0.1100</td>
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<tr>
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<td>0.0544***</td>
<td>0.0396*</td>
<td>0.0899</td>
<td>0.0490</td>
<td>0.0603**</td>
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<tr>
<td>Total Assets</td>
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<td>0.1985***</td>
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<td>Nonperf. Loans</td>
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<td>-0.1406*</td>
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Table 3: Regression Analysis of Shareholder Value Efficiency.

This table reports results from regressions of EVA scaled by lagged total assets on shareholder value efficiency ($\psi_{-eff}$) as well as a set of control variables. These include return on assets ($ROA$), leverage ($LEV_{RAG}$), the ratio of nonperforming loans to total loans ($NPL$) and bank size ($BK_{SIZE}$). $x_{-eff}$ and $\tau_{-eff}$ indicate cost and revenue efficiency respectively. $MA$ stands for managerial ability and has been computed following Demerjian, Lev, McVay (2012). SFA stands for stochastic frontier analysis, GFA stands for generalized frontier analysis. All regressions include year and bank fixed effects. T-statistics are reported in parentheses and stars indicate significance levels at 0.01 (***) , 0.05 (**) and 0.1 (*) levels. Standard errors are clustered by bank; all regressors are Z-transformed.

<table>
<thead>
<tr>
<th>Parameter (1)</th>
<th>(2)</th>
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<td>$\psi_{-eff}^{SFA}$</td>
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<td>0.0175***</td>
<td>0.0160***</td>
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<td>-0.00366***</td>
<td>-0.00195***</td>
<td>-0.00366***</td>
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<td>-0.00366***</td>
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<td>0.000991***</td>
<td>0.00217***</td>
<td>0.000991***</td>
<td>0.00217***</td>
<td>0.000991***</td>
<td>0.00217***</td>
<td>0.000991***</td>
<td>0.00217***</td>
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<tr>
<td>$MA$</td>
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<td>0.00427***</td>
<td>0.00359***</td>
<td>0.00427***</td>
<td>0.00359***</td>
<td>0.00427***</td>
<td>0.00359***</td>
<td>0.00427***</td>
<td>0.00359***</td>
<td>0.00427***</td>
<td>0.00359***</td>
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<tr>
<td>$ROA$</td>
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<td>0.0473***</td>
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<td>0.0375***</td>
<td>0.0473***</td>
<td>0.0412***</td>
<td>0.0375***</td>
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<tr>
<td>$NPL$</td>
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<td>-0.000120*</td>
<td>-0.00120*</td>
<td>-0.000120*</td>
<td>-0.00120*</td>
<td>-0.000120*</td>
<td>-0.00120*</td>
<td>-0.000120*</td>
<td>-0.00120*</td>
<td>-0.000120*</td>
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<td>0.025***</td>
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<td>$LEV_{RAG}$</td>
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<tr>
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</tbody>
</table>
This table reports the contribution to adjusted $R^2$ made by each variable in the regressions in Table 3. Specifically, each cell indicates how much the regressor contributes to the explanatory power of the regression indicated by the column heading. The contribution to adjusted $R^2$ was computed as $C_j = \frac{R^2 - R^2_j}{R^2}$, where $C_j$ is the contribution of the $j$th variable, $R^2_j$ is the adjusted $R^2$ computed without that variable and $R^2$ is the total adjusted $R^2$. $\psi - \text{eff}$ represents shareholder value efficiency, while $x - \text{eff}$ and $\tau - \text{eff}$ indicate cost and revenue efficiency. SFA indicates stochastic frontier analysis. GFA indicates generalized frontier analysis (asymmetry parameter $\alpha = 1000$). $MA$ stands for managerial ability and has been computed following Demerjian, Lev, McVay (2012).

<table>
<thead>
<tr>
<th>Parameter</th>
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<td>$\psi - \text{eff}_{GFA}$</td>
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<td>0.1</td>
<td>0.2</td>
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</table>
Table 5: Correlation of Bank Cost Efficiency with Nonfrontier Performance Measures.

This table reports Spearman rank correlations between different efficiency measures and nonfrontier indicators of performance for the full population as well as split by size into the smallest 50%, the medium 40% and the largest 10% of banks. Stars indicate significance levels at 0.01 (***) , 0.05 (**) and 0.1 (*) levels. SFA indicates stochastic frontier analysis. DEA indicates data envelopment analysis. GFA indicates generalized frontier analysis (asymmetry parameter \( b = 1000 \)). ROA represents return on assets, EP denotes economic profit, EVA denotes economic value added.

<table>
<thead>
<tr>
<th>Correlates</th>
<th>Panel A: All Banks</th>
<th>Panel B: Small Banks 0-50%</th>
<th>Panel C: Medium Banks 50-90%</th>
<th>Panel D: Large Banks 90-100%</th>
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</thead>
<tbody>
<tr>
<td>ROA</td>
<td>+ 0.0085</td>
<td>0.1750***</td>
<td>0.0806**</td>
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<tr>
<td>Total Cost</td>
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<td>-0.6621***</td>
<td>-0.2515***</td>
<td>-0.5287***</td>
</tr>
<tr>
<td>Total Revenue</td>
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<td>0.1171**</td>
<td>0.2299**</td>
<td>0.0057</td>
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<td>Total Assets</td>
<td>± 0.1483***</td>
<td>-0.0401***</td>
<td>0.2554***</td>
<td>0.0074</td>
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<tr>
<td>Equity</td>
<td>± 0.1483***</td>
<td>-0.0401***</td>
<td>0.2554***</td>
<td>0.0074</td>
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<tr>
<td>Total Assets</td>
<td>± 0.1483***</td>
<td>-0.0401***</td>
<td>0.2554***</td>
<td>0.0074</td>
</tr>
<tr>
<td>EVA</td>
<td>+ 0.0061</td>
<td>0.1171**</td>
<td>0.2299**</td>
<td>0.0057</td>
</tr>
<tr>
<td>EP</td>
<td>± 0.1483***</td>
<td>-0.0401***</td>
<td>0.2554***</td>
<td>0.0074</td>
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<tr>
<td>Total Assets</td>
<td>± 0.1483***</td>
<td>-0.0401***</td>
<td>0.2554***</td>
<td>0.0074</td>
</tr>
<tr>
<td>Cap. Charge</td>
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<tr>
<td>Total Assets</td>
<td>± 0.1483***</td>
<td>-0.0401***</td>
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<tr>
<td>Liquid Assets</td>
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<td>-0.1139*</td>
<td>0.2072***</td>
<td>-0.0030</td>
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<tr>
<td>Total Assets</td>
<td>± 0.1483***</td>
<td>-0.0401***</td>
<td>0.2554***</td>
<td>0.0074</td>
</tr>
<tr>
<td>Nonp. Loans</td>
<td>± 0.0896***</td>
<td>-0.1139*</td>
<td>0.2072***</td>
<td>-0.0030</td>
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<tr>
<td>Total Loans</td>
<td>± 0.1483***</td>
<td>-0.0401***</td>
<td>0.2554***</td>
<td>0.0074</td>
</tr>
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