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Efficient, profitable and safe banking: an oxymoron? Evidence from a panel VAR approach

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Abstract

Efficiency is considered a key factor when evaluating a bank's performance. Moreover, efficiency enhancement is an explicit policy objective in the Single Market Directive of the European Commission. But efficiency improvements may come at the expense of deteriorating bank profits and excessive risk-taking. Both the quantitative effects and dynamic reactions of performance in response to efficiency improvements remain often unclear on both theoretical and empirical grounds. We analyze the dynamic relations between efficiency and performance in the German banking market. To this end we use panel data for all German banks for the years from 1993 to 2004 and estimate impulse response functions (IRF) derived from a vector autoregressive model. The IRF estimate the response of a shock in efficiency on profits or default probabilities. The former is estimated with stochastic frontier analysis, the latter is estimated with a hazard rate model. The results indicate that a positive unit shift in efficiency reduces the probability of default and increases profits. On the one hand, we find evidence that the long-run impact of profit efficiency on risk is larger than for cost efficiency. However, cost efficiency impacts with a shorter time lag on the probability of default. On the other hand, cost efficiency has on average a slightly larger impact on profits than profit efficiency.

Keywords: Bank performance, efficiency, bank failure, vector autoregression, performance forecast.

JEL: C33, C53, D21, G21, G33, L25

Non-technical summary

Cost and profit efficiency are widely recognized as important determinants of bank profitability and risk. Empirical evidence on the magnitude and the dynamics of these interdependencies, however, is virtually absent from the financial economics literature. In this study we estimate the profitability and risk reactions to efficiency shocks (and vice versa). To this end we use a panel of German universal banks between 1993 and 2004. A major problem in the model building process is that efficiency itself is also driven by profitability and risk. We therefore develop a panel vector autoregression model in order to account for endogeneity.

With the exception of profitability, measured as return on risk-weighted assets, we cannot directly observe the variables of interest. Therefore, we estimate cost and profit efficiency (CE and PE) with stochastic panel frontier analysis and use a bank's probability of default estimated with a hazard rate model ($Score$) as a proxy for risk.

Both measures are employed in a two equation dynamic panel model. From that we obtain coefficients for efficiency and performance equations regressed on lagged endogenous, performance and efficiency measures, respectively. From here we calculate impulse response functions (IRF) to quantify the magnitude and dynamics of each efficiency-performance pairing for all four measures.

We find that positive efficiency shocks significantly improve bank performance in subsequent periods. The effect of PE improvements on risk and of CE improvements on profitability are largest. Efficiency shocks impact with a time lag of only two years on profits and decay rapidly thereafter. The same applies for the responses of risk to cost efficiency shocks, whereas responses to profit efficiency shocks display higher lags of roughly four years. Compared to cost efficiency the overall effects from profit efficiency shocks on risk are larger. Hence, banks that require immediate action to reduce their probability of default may want to focus on improving their cost management skills. Long-term reductions of risk seem more adequately targeted by enhancing profit efficiency.

In sum, improving efficiency reduces risk and boosts profits. This result is robust across various specification choices and IRF indicate that the effects are rather persistent.

Nichttechnische Zusammenfassung

Kosten- und Gewinneffizienz werden im allgemeinen als wichtige Bestimmungsgrößen für die Ertragskraft und das Risiko einer Bank angesehen. Es gibt allerdings kaum empirische Ergebnisse, die diesen Einfluss nachweisen oder in ihrem Ausmaß und ihrer Dynamik bestimmen. Der vorliegende Beitrag hat das Ziel, den Einfluss beider Effizienzarten auf die Ertragskraft einerseits und das Risiko andererseits zu messen. Dazu wird ein Panel aller deutschen Universalbanken aus den Jahren 1993 bis 2004 herangezogen.

Ein Problem bei der Schätzung ergibt sich daraus, dass auch die Ertragskraft und das Risiko die Kosten- und Gewinneffizienz beeinflussen. Um diesen Endogeni-täten Rechnung zu tragen, wird ein Panel-Vektorautoregressives Modell entwickelt. Ein weiteres Problem entsteht dadurch, dass die verwandten Größen in der Studie mit Ausnahme der Ertragskraft, welche hier mit dem auf die risikogewichteten Aktiva bezogenen Gewinn gemessen wird, nicht direkt beobachtbar sind und deshalb separat modelliert werden müssen. Die Kosten- und Gewinneffizienz werden mit einer stochastischen Panel-Frontieranalyse bestimmt. Das Risiko einer Bank wird mit der Ausfallwahrscheinlichkeit aus einem Hazardratenmodell gemessen. Aus den Variablen wird ein Zweigleichungs-Vektorautoregressives Modell geschätzt, jeweils mit einer Effizienzvariablen (alternativ Kosten- oder Gewinneffizienz) und einer Performancevariablen (Ertragskraft oder Risiko). Um die Auswirkungen von Effizienzschocks auf die Performancevariablen zu bestimmen, werden aus den Schätzergebnissen Impuls-Response-Funktionen für 10 Zeitperioden berechnet.

Die Ergebnisse zeigen, dass positive Effizienzschocks in den Folgeperioden mit einer signifikant höheren Performance einhergehen. Besonders hoch sind die Wirkungen von Gewinneffizienz auf das Risiko und von Kosteneffizienz auf die Ertragskraft. Auf die Ertragskraft wirken Effizienz-Schocks zwar mit einer vergleichsweise geringen Verzögerung von etwa zwei Jahren, verlieren aber danach rasch an Wirkung. Auf das Risiko wirken Kosteneffizienz-Veränderungen ebenfalls rasch. Gewinneffizienzschocks hingegen entfalten hier ihre Hauptwirkung auf die Risikosituation erst nach etwa vier Jahren und sind in der Summe länger anhaltend und wirkungsvoller als Kosteneffizienzschocks. Eine mögliche Schlussfolgerung ist, dass Maßnahmen zur Steigerung der Kosteneffizienz geeignet sind, auch sehr kurzfristig eine Verminderung der Ausfallwahrscheinlichkeiten zu bewirken, während sich substanzielle Risikoreduzierung nachhaltig eher mittels einer Verbesserung der Gewinneffizienz erzielen lässt.

Zusammenfassend bestätigen unsere Ergebnisse, dass Effizienzverbesserungen zu einem geringeren Risiko und einer höheren Ertragskraft beitragen. Dieser Befund zeigt sich robust in allen unterschiedlichen Spezifikationen unserer Untersuchung.

Contents

Efficient, Profitable and Safe Banking: An Oxymoron? Evidence from a Panel VAR Approach[1]

"An efficient Internal Market is essential for a prosperous economic future, for our jobs and our living standards."
Charlie McCreevy, EU commissioner

oxymoron
/oksi**mor**on/
noun a figure of speech or expressed idea in which apparently contradictory terms appear in conjunction
ORIGIN from Greek oxumoros 'pointedly foolish'.
Oxford English Dictionary

1 Introduction

On January 1, 1993 the Second Banking Directive was implemented by national governments in Europe. It's aim is to enhance competition and the efficient provision of financial products and services in Europe (Benink, 2000). The objectives of the European Commission (EC) have changed little since: to foster competition as to further boost the *efficiency* of Europe's financial industry (EC, 2005). Regulators and practitioners, in turn, are also concerned with the *performance* of banks. In particular, financial stability reviews by the Deutsche Bundesbank (2006) and the European Central Bank (2006) monitor profitability and risk.[2]

But to a large extent the relation between bank efficiency and performance remains a conundrum. After all, one fundamental theorem of welfare economics necessitates perfect competition for efficiency. More efficiency-enhancing competition reduces prices to marginal costs, thereby reducing banks' profits or even forcing them out of the market. Alternatively, banks on the brink of exit may be inclined to take excessive risks in an attempt to gamble for resurrection when exposed to constant pressure to improve efficiency (Amel et al., 2004). Consequently, one may ask whether we can have efficiency and financial stability as measured by profitable yet reasonably risky banks at the same time (Gorton and Winton, 1998)?

A number of studies theorizes on the relation between competition and financial

[1] m.koetter@rug.nl (M. Koetter) and daniel.porath@wiwi.fh-mainz.de (D. Porath). We would like to thank participants at the Economic Seminar Series at the University of Tübingen and the Supervision Seminar Series at Deutsche Bundesbank. We are grateful to Claudia Buch, Ferre de Graeve, Sandra Eickmeier, Frank Heid, Robert Jung and Laura Spierdijk for helpful comments. This paper is part of a research project funded by the 'Stiftung Geld und Währung'. The paper represents the authors' personal opinions and not necessarily those of the Deutsche Bundesbank. We are grateful for the provision of data. Any remaining errors are, of course, our own.

[2] The use of the words profit and risk in the ECB's latest Review provides anecdotal evidence on these proxies' importance: 847 and 2,158 times, respectively. Efficiency is mentioned 1,719 times and thus of importance, too. In contrast, the title word "stability" occurs only 589 times.

stability implicitly assuming the former to enhance efficiency.[3] Two views juxtapose each other. For example, Allen and Gale (2000; 2004) advocate the concentration-stability notion. They argue that atomistic banking markets, and hence *ceteris paribus* more competitive and efficient ones, are more prone to crises for two reasons. Competitive markets are characterized by poor profitability, which implies a lack of buffer to absorb adverse shocks. In addition, supervision can be executed more effectively for a low number of banks compared to monitoring a system of many intermediaries. This view is contrasted by the concentration-fragility view. Boyd and De Nicolo (2005) also posit that increased concentration boosts profits but highlight that market power also changes the conduct of banks. Specifically, their model results in excessive risk-taking of banks if higher interest rates can be imposed on customers due to market power. Beck et al. (2006) tests the relation between competition (as measured by concentration) and banking system fragility (as measured by banking crises) between 1980 and 1997. In short, they define the latter as periods when mean shares of non-performing total loans exceeded 10%. They report results in line with the concentration-stability hypothesis, indicating that further concentration as a response to increased competition actually stabilizes financial systems. However, Boyd and De Nicolo (2005) note that approaches using relatively crude macroeconomic proxies for risk and competition may fail to capture important dynamics across banks. In this vein, they conclude that empirical evidence, especially at the macroeconomic level, does not yield a clear picture so far.

Indeed, the micro economic variation across firms, and even products, is at the heart of an important contribution by Goodhart et al. (2006). They depart from the most common assumption of a representative agent but allow for heterogenous agents and product markets in banking. The suggested general equilibrium model combines individual bank behavior, especially risk-taking, at the microeconomic level with monetary and regulatory policy at the macroeconomic level. The latter determine interest rates and costs of bank default. One core result is the endogenous possibility of trade-offs between financial stability and economic efficiency. In a companion paper, they forward numerical solutions from simulation exercises with a simplified version of the complete model (Goodhart et al., 2004). Results corroborate the previous conclusion of a possible goal conflict between efficiency and performance. First, they find that monetary and regulatory policy are non-neutral and influence both bank profitability and default penalties. Second, they find that at the microeconomic level, heterogeneous agents and banks react differently to shocks. However, the authors caution carefully that especially the latter set of results depends considerably on chosen starting values for their simulations and develop in a hard to predict fashion. This suggests that the evolution of different aspects of banking business, for example risk-taking on the one hand and efficiency on the other, depend in a complex manner upon each other.

Apparently, the exact dynamics of how bank efficiency and performance relate to

[3] For example, theoretical models by Gorton and Winton (1998) and Perottia and Suarez (2002) on the relation between competition and stability are both motivated by stipulating that deregulation fosters competition and thereby the efficiency of the banking system. Empirically, the relation between (market) structure, (firm) conduct and performance represents an extensive literature in it's own right. European banking market SCP studies are Bikker and Haaf (2002a,b) and Hempell (2004). However, the SCP paradigm in itself is not beyond debate, see Bikker et al. (2006) for a critical evaluation.

each other remain contradictory at the least if not unclear. Despite the differences in findings, Allen and Gale (2004), Boyd and De Nicolo (2005) and Goodhart et al. (2004) are united in their call for further research to provide empirical evidence given the lack of consensus on theoretical grounds. Unfortunately, empirical tests on the relation between efficiency and performance of banks are to a large extent also reflections of the described ambiguity as we illustrate shortly. Therefore, we suggest in this paper an alternative, agnostic empirical approach to provide evidence if aiming at improved efficiency, higher profitability and reasonable risk at the same time indeed is an attempt to square the circle.

To this end we use a panel dataset of German banks. First, we estimate cost and profit efficiency scores with financial data. (In)efficiency is the deviation from an optimal cost and profit obtained from stochastic panel frontier analysis (SFA) using financial data of individual banks. Second, we observe profitability also from bank-specific financial accounts. Third, we develop a hazard model to estimate a bank's risk as the probability of default (PD). The hazard model in our context is a rating model, which uses the correlation between a set of risk drivers observed in a specific period and the default state observed some time after. Thus, we measure efficiency and performance directly at the firm level instead of having to follow the theoretical detour via competition.

Next, we need to appropriately deal with encountered endogeneity between efficiency and performance. Endogeneity means that efficiency and performance affect each other simultaneously. The contemporaneous feedback implies that shocks in efficiency impact on performance and shocks in performance impact on efficiency. An example of an efficiency shock at the macroeconomic level is the implementation of directives enhancing competition, such as the abolishment of guarantee and maintenance obligations by the government (*"Gewaehrtraegerhaftung"* and *"Anstaltslast"*) for savings banks in 2004 (IMF, 2004). At the bank level, a typical efficiency shock is a restructuring program launched in period t. Presumably, such a program will not only affect efficiency but also profits of the current period. A typical performance shock, on the other hand, is an economic downturn in a sector to which a bank's credit portfolio is exposed. The downturn will cause high loan loss provisions, lower profits and a higher PD. Contemporaneously, the performance shock may impact on efficiency, when the downturn induces the bank to enter in new sectors or markets. The examples show that estimators for the impact from efficiency on performance have to be derived from a simultaneous model. To our knowledge this paper is the first to explicitly address this simultaneity between efficiency, profits and risk.

A look on the data generation process confirms the necessity to account for the interdependence of risk, return and efficiency. Performance and efficiency are both calculated from data which refer to the same financial statement. For accounting reasons, the different balance sheet and profit and loss account positions are correlated. For example, accounting rules imply that loan loss provisions are linked to profits, which in turn are linked to equity capital. Data from all three accounts of the example typically enter both, the efficiency variable and the performance variable (PD or profits). Thus already from a static perspective, efficiency, PD and profits are a conglomerate of correlated variables and are therefore correlated among themselves.

A third characteristic of our study is to account for dynamic interdependencies. We consider a variety of lagged relationships between efficiency and performance since the effects from either shock will not be confined to one period only. In contrast, we expect complex patterns of contemporaneous and lagged interactions between both variables, which can hardly be modeled with *a priori* knowledge. A way to deal with endogeneity and complex lag structures are vector autoregression (VAR) models. VAR models were originally proposed by Sims (1980) as an alternative to structural models. The major difference between VAR models and structural models lies in the model building process. Structural models heavily rely on *a priori* knowledge, whereas VAR models are more data-driven.[4] In our case, VAR models have benefits compared to structural models because the relationship between performance and efficiency is expected to be complex. At the same time there is little (or no) *a priori* knowledge about the exact lag structure. In the following we therefore estimate a (two-variable) VAR model for efficiency and performance.

The rest of the paper is structured as follows. We set out with a brief review of previous empirical work on the relation between efficiency and performance in section 2. In section 3, we introduce our theoretical concepts for estimating efficiency, profits and risk and the IRF. In section 4 we describe the individual bank data provided by the Bundesbank and the regional macroeconomic data which we additionally use. In section 5 we present and discuss our results. We conclude in section 6.

2 Empirical work on efficiency and performance

In light of our study, empirical work on bank efficiency and performance can broadly be classified into two groups. Studies that explain bank performance as a function of efficiency and studies that specify an efficient frontier conditional on performance. This observation alone indicates the necessity to account for interdependency on the one hand and cautions to draw inference on causal relationship on the other.

Performance and efficiency The literature on bank PD estimation to approximate risk is abundant and dates back to the 1970s[5] First generation bank rating models focused on cross-section techniques, such as discriminant analysis and logit regression (Sinkey, 1975; Martin, 1977; Altman, 1977). More recent studies use methods for panel or duration data (Cole and Gunther, 1995; Estrella et al., 2000; Shumway, 2001). To our knowledge, Wheelock and Wilson (1995) provide for the first time evidence on the direct relation between efficiency and banking risk. On the basis of financial ratios, which also include profitability, and historical default data they predict bank failures of Kansas state chartered banks between 1910 and 1928. They use non-parametric, linear programming techniques to estimate firm-specific efficiency much more directly compared to earlier studies (Charnes et al., 1978).

[4]Structural models aim to fit parsimonious models because coefficient restrictions are necessary to identify the model. Imposing restrictions in our model is problematic due to unknown feedback relations between efficiency and performance and, thus, potentially biased results. To avoid 'unrealistic restrictions', VAR models estimate an unrestricted reduced form of the underlying structural model, which allows for a maximum of feedback relations. Identification of the structure is then achieved by imposing a minimum number of restrictions. Hence, VAR models are parsimonious in the number of restrictions, but not in the number of reduced form coefficients estimated. This allows the analysis of feedback relations and is therefore particularly suited for our purpose.

[5]A comprehensive overview on rating methods is (King et al., 2005).

Their results yield that inefficiently managed banks are more likely to fail, thus providing evidence that higher efficiency reduces the risk of instability in the banking industry.[6] In turn, Pasiouras and Kyriaki (2006) seek to identify the determinants of commercial bank profitability in 15 EU countries between1995 and 2001. They motivate their research by pointing out that "adequate" earnings are necessary to ensure the stability and growth of banks and, ultimately, the economy. They specify a fairly a-theoretical reduced profit equation that includes bank-specific variables and controls for macroeconomic conditions and ownership type. In line with other bank profitability studies (Berger, 1993; Demirgüç-Kunt and Maksimovic, 2002), they find that better capitalization, i.e. less risky banks, has a positive impact on return on assets (ROA) and less efficient banks to exhibit also lower profitability.

Efficiency and performance Since it's inception in the late 1970s, the bank efficiency literature expanded beyond limits possibly reviewed within the scope of this paper.[7] However, only relatively few studies followed a suggestion by Mester (1993, 1996) to control for performance, especially risk, during estimation. Rather than including controls in the frontier itself, some studies attempt to identify what is frequently coined determinants of efficiency by means of second stage analysis. They ususally report a positive relation between efficiency and profitability proxies, such as return on assets or equity (ROE) and interest margins, and a negative relation with risk proxies, such as poor capitalization or high non-performing loan shares (Vander Vennet, 2002; Pastor and Pastor, 2002; Casu and Molyneux, 2003; Carbo and Williams, 2003; Girardone et al., 2004; Das and Ghosh, 2006).

A first observation is that results are frequently inconsistent. Girardone et al. (2004) report insignificant coefficients for profitability in many sub-samples and that higher interest rate margins are negatively correlated with efficiency. Similarly, Williams and Gardener (2003) find that efficiency depends negatively on interest rate mark-up's. This contradicts other findings of higher profits to be related to higher efficiency. Likewise, results obtained by Casu and Molyneux (2003) yield insignificant relations between risk and efficiency and significantly positive influences of ROE on efficiency for only two years in their sample. Das and Ghosh (2006) find a significantly positive effect of ROA on efficiency but carefully note that the former is endogenously related to efficiency and therefore instrument ROA. But in their discussion it remains unclear why endogeneity is limited to ROA. We argue that any indicator, either performance or efficiency, is based on financial annual reports and may thus suffer from similar problems.

This relates to a second critique on studies using second stage regression to "explain" efficiency.[8] Any study of bank-specific data ultimately extract information

[6]Most subsequent papers confirm that efficiency measures are significantly correlated with lower probabilities of default and market exit through mergers in numerous countries (Wheelock and Wilson, 2000; Focarelli et al., 2002; Koetter et al., 2006). However, studies using multiple frontier efficiency measures report significant correlations for only a some (Worthington, 2002).

[7]Excellent introductions to parametric and non-parametric frontier methods are Kumbhakar and Lovell (2000) and Ali and Seiford (1993), respectively. The development of bank efficiency applications is reviewed by Berger et al. (1993), Berger (2003) and Amel et al. (2004).

[8]Kumbhakar and Lovell (2000) note two further problems. First, 2^{nd} stage regressors are assumed to be uncorrelated with frontier elements in the 1^{st} stage. If they are not, efficiency estimates regressed in the 2^{nd} stage are biased. Second, efficiency is identically distributed by assumption in the 1^{st} stage. Estimation of a functional relationship in a 2^{nd} stage is then paradoxical.

from the identical data generation process. Put differently, measures for risk, profitability, efficiency and other indicators all emerge from bank's annual reports. Only few efficiency studies attempt to address this issue explicitly. Kwan and Eisenbeis (1997) estimate a simultaneous system of four equations to account for both risk and efficiency being endogenously dependent. Three equations capture different aspects of risk and one specifies efficiency as a function of the former three. They find that less efficient banks are more inclined to take risks. At face value, one may conclude that competitive pressure to improve efficiency may ignite excessive risk taking. But Kwan and Eisenbeis (1997) also report that higher capitalization, i.e. less risky banking, positively influences efficiency. They carefully conclude that their results do not only suffer from low explanatory power in statistical terms, but also that the economic inconsistency of results warrants future work on the presumably more intricate relation between risk and efficiency.

In sum, empirical evidence at the microeconomic level measures risk, efficiency and profitability more directly compared to the macroeconomic level. However, results are mixed and the earlier lack of theoretical guidance as to the direction of causal relations remains. The endogeneity inherent in the data generation process is usually neglected, let alone the dynamics of a change in efficiency on performance. Therefore, we derive first auxiliary measures of efficiency and performance as to quantify subsequently the dynamic effects of both respective measures with a panel VAR approach.

3 Variable Generation and Methodology

3.1 Efficiency

Efficiency analyses benchmark individual banks relative to a market cost or profit frontier (Amel et al., 2004; Berger, 2003). Theoretically, the main function of a bank i is to channel savings from surplus units to investors in need for funds (Sealey and Lindley, 1977). Assuming perfect factor markets and cost minimization as objective, banks demand input quantities x at given factor prices w to produce outputs y such that costs C are optimal. To account for heterogenous risk profiles of banks, we follow the convention in the efficiency literature and condition the production technology $T(y, x, z)$ on equity capital z. Solving this cost minimization problem yields an optimum cost function $C_i^* = f(y_i, w_i, z_i)$. Observed costs are higher than optimal costs either due to random noise or due to inefficiency. Cost inefficiency results from the employment of too large quantities of factors given output and/or a sub-optimal input mix given respective prices.

Humphrey and Pulley (1997) argue that cost efficiency alone fails to evaluate the ability of a bank to generate profits. They emphasize the necessity to study profit efficiency, too. Most profit efficiency studies use their alternative profit model where banks possess some output market power. This assumption is appropriate for German banking given the regional demarcation of markets (Koetter et al., 2006) and evidence of prevailing market power in regional credit markets (Hempell, 2004; Fischer and Pfeil, 2003). Banks maximize profit before tax, $PBT = py - wx$, subject to $T(y, x, z)$ and, in addition, a pricing opportunity constraint $H(p, y, w, z)$, where

p denote output prices. Note, that the inefficiencies arising from the cost side are considered in this model, too. Banks choose input quantities and output prices and profit inefficiency leads to lower than optimal profits $PBT_i^* = f(y_i, w_i, z_i)$. Since we allow banks some price setting discretion within the boundaries of $H(\bullet)$, both cost and alternative profit frontiers depend on the identical set of independent variables.

We use stochastic frontier analysis (SFA) to estimate cost and profit functions as well as cost and profit efficiency (CE and PE).[9] Recall that we are interested in the long-run impact of efficiency shocks on performance on the one hand and long-run reactions of efficiency to performance shocks on the other. It is therefore crucial to specify panel stochastic frontiers that allow for time-variant inefficiency. We use the translog functional form to write a cost frontier as:[10]

$$\ln C_{it} = \alpha_i + \sum_{j=1}^{J} \alpha_j \ln x_{ijt} + \frac{1}{2} \sum_{j=1}^{J} \sum_{k=1}^{K} \alpha_{jk} \ln x_{ijt} \ln x_{ikt} + \varepsilon_{it}. \quad (1)$$

Here x consists of outputs y, input prices w, control variables z and a time trend t. In any year t, a bank i can deviate from optimal cost C due to random noise v_{it} or inefficiency u_{it}. To distinguish these two effects, we specify a composed total error ε_{it}. Cost inefficiency leads to above frontier costs and the total error is $\varepsilon_{it} = v_{it} + u_{it}$. Profit inefficiency leads to lower than optimal profits, thus leading to $\varepsilon_{it} = v_{it} - u_{it}$. The random error term v_{it} is assumed iid with $v_{it} \sim N(0, \sigma_v^2)$ and independent of the explanatory variables. The inefficiency term is iid with $u_{it} \sim N|(0, \sigma_u^2)|$ and independent of the v_{it}. It is drawn from a non-negative distribution truncated at zero. The α_i's are allowed to be correlated with y_{it}, w_{it} and z_{it} (Greene, 2005).

Most studies estimate bank efficiency over multiple years. But only few exploit the additional information contained in longitudinal data. Parameters of equation (1) are estimated instead as a pooled cross-section. This is problematic since this approach implicitly assumes that individual bank's production is independent over time, inefficiency u_{it} is assumed to be independent of the regressors and point estimates of inefficiency are not consistent (Kumbhakar and Lovell, 2000). In turn, most panel frontier application treat efficiency either as time-invariant (Bauer et al., 1993) or impose substantial structure on the evolution of efficiency over time (Battese and Coelli, 1988). In light of our interest to assess the long-run behavior of performance and efficiency, both model classes are inappropriate. First, we assume by construction that shocks to performance lead to changes in efficiency. Hence, any time-invariant modeling of efficiency is ill-suited to our ends. Second, we hypothesize that efficiency shocks, such as restructuring programs, are likely to cause deteriorating efficiency first and to yield gains only after some implementation period. Consequently, the development pattern of efficiency should be allowed to be non-monotonic.

Therefore, we use what Greene (2005) coins a 'true' fixed effects frontier model, which has two main advantages. First, efficiency can develop unrestrictedly over

[9] Linear programming approaches are more sensitive to outliers due to the neglect of random noise. Given well-known measurement problems with banking data (Mountain and Thomas, 1999), we opt here for parametric methods.

[10] In case of the profit frontier only the dependent variable changes from to $lnPBT$.

time. The u_{it} is not parameterized in any way as a function of time and may thus exhibit virtually any development pattern for a given bank i. Second, systematic differences other than inefficiency enter the bank-specific effect α_i. In contrast to most previous estimators, the latter is identified separately from the inefficiency term u_{it} (Polachek and Yoon, 1996). Greene (2005) demonstrates by a Monte Carlo experiment a substantially improved performance compared to previous panel estimators.

We use the conditional distribution of u given ε to obtain bank-specific efficiency measures (Jondrow et al., 1982). A point estimator of technical efficiency is given by the mean of u_{it} given ε_{it}. Cost and profit efficiency are calculated as $\exp(-u_{it})$ and equal one for a fully efficient bank. In the profit case, PE of 0.9 implies that a bank realized only 90% of optimal profits that could have been realized with the identical production plan. Likewise, in the cost case a CE score of 90% indicates that the bank could have produced the identical output vector with 10% less operating cost.

3.2 Performance

We evaluate bank performance along two dimensions: profits and risk. The former can be directly observed from financial accounts and we define our profitability measure profits before tax PBT relative to risk-weighted assets RWA as:

$$ROA_{it} = \frac{PBT_{it}}{RWA_{it}} \tag{2}$$

In contrast to profitability, risk is not observable and has to be estimated with an appropriate model. We define risk as a bank's default risk which can be assessed with the probability of default (PD). Porath (2006) uses a time-discrete hazard model to estimate the PD of German savings banks and credit cooperatives with a sample similar to ours. Concerning the discussion of different rating models and the final choice we therefore refer to his study and estimate a similar time-discrete hazard model.

Like any rating model, a hazard model transforms a set of (mostly) bank-specific covariates observed in a given year t into the PD. The rating process can be thought of as a two-step procedure where the first step yields the score as a weighted sum of the covariates. The second step transforms the score into the PD with an appropriate link function. The score weights can be estimated with historical data of the covariates observed in t and the actual state of default in $t+1$. In such a setting the average PD of all banks in t is a predictor for the default rate of all banks in $t+1$. The individual bank PD in a given year PD_{it} is the probability that bank i defaults within one year. The exact definition of default is largely determined by the available data. In our dataset a default event is any event indicating that the bank is in danger of ceasing to exist as a going concern.[11] This definition corresponds to the supervisory objective to prevent insolvencies.

Since Porath (2006) finds no significant differences between different link functions we use the logit link function, which is the most easiest to handle. We write the time-discrete hazard model as:

[11] We provide details in section 4.

$$PD_{it} = \frac{e^{Score_{it}}}{1 + e^{Score_{it}}}. \quad (3)$$

Here, PD_{it} denotes the probability that bank i will default in period $t+1$ and $Score_{it}$ is the score of bank i in period t. $Score_{it}$ is calculated from

$$Score_{it} = \sum_{j=1}^{n} \beta_j X_{it,j} + \lambda_{i0} + \lambda_{0t}. \quad (4)$$

Equation (4) is a linear function of the set of j covariates $X_{it,j}$ observed for bank i in period t and weighted with the parameters β_j. Additionally, a set of time dummy variables λ_{0t} enters equation (4) in order to account for unobserved time-effects. The unobserved individual effects λ_{i0} are assumed to be random because the alternative fixed-effects model requires a change of status of the observed endogenous variable (Chamberlain, 1980). This would restrict the sample to defaulted banks.

Instead, the random-effects model permits the inclusion of the whole sample in the estimation. Here we use the population average model proposed by Zeger and Liang (1986). The population average model estimates equations (3) and (4) with the Generalized Estimating Equations (GEE) after replacing the (unobserved) variable PD_{it} with a dummy variable Y_{it+1}. Y_{it+1} takes the value of 1 if bank i defaults in period $t+1$ and the value 0 otherwise. The time lag of one year between the dummy variable and the covariates determines the forecast horizon.[12]

Our covariate selection is in line with other bank rating studies (King et al., 2005). We first allocate covariates to different categories of risk drivers, where the latter follow the CAMELS taxonomy used by U.S. supervisory authorities and other central banks to monitor and assess banks. The categories comprise **C**apitalization, **A**sset quality, **M**anagement skill, **E**arnings, **L**iquidity and **S**ensitivity to market risk. We then select the model which maximizes the discriminative power under the restriction that it contains at least one variable of each CAMELS category. We measure the discriminative power by the area under the Receiver Operating Characteristics (ROC) curve. Typical to statistical rating analysis our dataset contains a large set of similar variables. Capitalization, for example, can be measured with many alternative ratios (e.g. Tier I capital per risk weighted assets , balance sheet equity capital per balance sheet total, Tier II capital divided by risk weighted assets etc.) which are variants of the same risk driver. In order to avoid multicollinearity, we additionally require that the model does not contain variants of the same risk driver.[13]

[12]The GEE method accounts for the unobserved individual correlation with the help of a working correlation matrix which enters the estimation. We specify that all observations of one bank have the same correlation, which is the standard exchangeable working correlation. The estimators are asymptotically consistent even if the working correlation matrix is not correctly specified (Hosmer and Lemshow, 2000).

[13]Additionally, we analyze the stability of the model with the help of hold-out samples and separate estimations for different groups of banks.

3.3 Panel Vector Autoregressive Model

We first estimate the reduced form of the model. Since our data is a panel of individual bank observations we have to estimate the reduced form with dynamic panel estimation techniques. This means that we regress all endogenous variables on the lagged endogenous variables. The reduced form VAR model is a stochastic multi-equation system. We obtain parameters by regressing the endogenous variables on the whole set of lagged endogenous variables. Analyzing efficiency and performance results in a two-equations VAR with the following structure:

$$Eff_{it} = \sum_{j=1}^{J} \alpha_{11j} Eff_{it-j} + \sum_{j=1}^{J} \alpha_{12j} Perf_{it-j} + \lambda_{1i0} + \lambda_{10t} + e_{1it} \quad (5)$$

$$Perf_{it} = \sum_{j=1}^{J} \alpha_{21j} Eff_{it-j} + \sum_{j=1}^{J} \alpha_{22j} Perf_{it-j} + \lambda_{2i0} + \lambda_{20t} + e_{2it} \quad (6)$$

Here, Eff_{it} and $Perf_{it}$ capture one of our efficiency variables, CE_{it} or PE_{it}, and performance variables, ROA_{it} or $Score_{it}$, respectively. We use $Score_{it}$ instead of PD_{it} because equations (5) and (6) are linear and the score is the linear transformation of the PD. Combining both variables for each category results in a total of four different specifications for equations (5) and (6). The maximum lag order J of the right-hand variables can be fixed with statistical means using the Akaike Information Criterion (AIC) and the outcome from diagnostic tests. To account for the unobserved time-effects λ_{10t} and λ_{20t} in equations (5) and (6), we further specify year-dummies. We handle the individual effects (λ_{10i} and λ_{20i}) by applying the GMM estimation of Arellano and Bond (1991) to equations (5) and (6). Note that the reduced from depicted in equations (5) and (6) is a pure forecast model. As noted for example by Sims (1980), this implies to refrain from analyzing individual coefficients of these estimations since we are primarily interested in error terms to calculate impulse responses below.[14]

To this end, we solve the estimated model and obtain the moving average (MA) representation. This is done by recursive elimination of lagged independent covariates. Note, that it is exactly this approach that necessitates stationarity of the dependent variables Eff_{it} and $Perf_{it}$ (Maddala and Wu, 1999; Im et al., 2003). The MA representation shows how the endogenous variables depend on the lagged residuals from the reduced form. The MA representation equates Eff_{it} and $Perf_{it}$ on present and past residuals e_1 and e_2 from the VAR estimation:

[14] One may regard the reduced form as a reflection of the true but unknown structural model. The latter contains additionally contemporaneous cross-terms of the respective sister equation. Thus, the structural model cannot be estimated due to a lack of identification and simultaneous equation bias, as would be the traditional approach to devise an explanatory model. Instead, a VAR approach proceeds by estimating and subsequently solving a reduced form. On this basis, the solution of the structural model is obtained thereafter.

$$Eff_{it} = a_{10} + \sum_{j=0}^{\infty} b_{11j} e_{1it-j} + \sum_{j=0}^{\infty} b_{12j} e_{2it-j} \tag{7}$$

$$Perf_{it} = a_{20} + \sum_{j=0}^{\infty} b_{21j} e_{1it-j} + \sum_{j=0}^{\infty} b_{22j} e_{2it-j} \tag{8}$$

Under the endogeneity assumption the residuals will be correlated and therefore the coefficients of the MA representation are not interpretable. The reason is that for correlated residuals the *ceteribus paribus* condition is not reliable when interpreting the coefficients. Thus, the residuals have to be orthogonalized. We orthogonalize the residuals by multiplying the MA representation with the Cholesky decomposition of the covariance matrix of the residuals. The orthogonalized, or structural, MA representation then is:

$$Eff_{it} = c_{10} + \sum_{j=0}^{\infty} \beta_{11j} \epsilon_{1it-j} + \sum_{j=0}^{\infty} \beta_{12j} \epsilon_{2it-j} \tag{9}$$

$$Perf_{it} = c_{20} + \sum_{j=0}^{\infty} \beta_{21j} \epsilon_{1it-j} + \sum_{j=0}^{\infty} \beta_{22j} \epsilon_{2it-j} \tag{10}$$

with

$$\begin{pmatrix} \beta_{11j} & \beta_{12j} \\ \beta_{21j} & \beta_{22j} \end{pmatrix} = \begin{pmatrix} b_{11j} & b_{12j} \\ b_{21j} & b_{22j} \end{pmatrix} \cdot \boldsymbol{P}, \begin{pmatrix} \epsilon_{1it} \\ \epsilon_{2it} \end{pmatrix} = \boldsymbol{P^{-1}} \cdot \begin{pmatrix} e_{1it} \\ e_{2it} \end{pmatrix} \tag{11}$$

Here $\boldsymbol{P}$ is the Cholesky decomposition of the covariance matrix of the residuals:

$$\begin{pmatrix} Cov(e_{1it}, e_{1it}) & Cov(e_{1it}, e_{2it}) \\ Cov(e_{1it}, e_{2it}) & Cov(e_{2it}, e_{2it}) \end{pmatrix} = \boldsymbol{P} \cdot \boldsymbol{P'} \tag{12}$$

The orthogonal residuals can be interpreted as shocks: ϵ_{1it} is a shock in efficiency and ϵ_{2it} is a shock in performance. The coefficients in the equations (9) and (10) are the impact multipliers and give the current response of the left-hand side variable to shocks occurring j periods ago. The MA representation with orthogonal residuals is also called impulse response function (IRF). The IRF gives the response of each variable included in the model to shocks from each of the variables for individual periods. For performance and efficiency the IRF provides estimates for the impact of efficiency on bank performance for the whole set of periods. The coefficients of the IRF are called impact multipliers because they measure the impact of a shock in a single period. By accumulating the impact multipliers for all periods we obtain the long-run multipliers which measure the overall response of performance to an efficiency shock. IRF and long-run multipliers answer exactly the questions raised in our study. We are primarily interested in the impact multiplier β_{21j}, which reflects the response of performance to a shock in efficiency for the different time horizons j. But since there are no theoretically motivated priors, it also conceivable that efficiency responds to shocks in performance. An example for the latter kind of shock could be a hike in credit defaults due to a random macroeconomic shock such as a flood in rural areas.[15] The upshot of our model is that we can assess the dynamic interdependencies between efficiency and performance with a minimum of restrictions imposed.

The latter results from the orthogonalization of the residuals from the observed residuals. The Cholesky decomposition involves imposing one restriction on the coefficients in the IRF because the matrix $\boldsymbol{P}$ results in an upper right element of zero. As can be seen from equation (11) this implies β_{120} in equation (7) to be zero. The kind of short-run restriction imposed depends on the order of the variables. When efficiency is the first variable in the model, we impose the restriction that performance shocks have no instantaneous impact on efficiency. In order to impose the instantaneous zero restriction on shocks from efficiency to performance, we additionally estimate a VAR model where the order of the variables is reversed and calculate the IRF function. In line with the previously mentioned lack of theoretical guidance, we chose two alternative short-run restrictions regarding zero contemporaneous impact multipliers of efficiency and performance, respectively: First, we assume that shocks in efficiency do not instantaneously impact on the performance variable. Second, we restrict shocks in performance to have no instantaneous impact on the efficiency variable.

Both restrictions have different implications for the interpretation of efficiency: In the first case, shocks in efficiency are identified as those shocks which do not immediately change the performance profile of a bank. In the second case, shocks in performance are only those shocks without immediate impacts on efficiency. To illustrate the implications of both different restrictions we again refer to the examples of a restructuring program (efficiency shock) and the bank specialized in a sector which experiments an economic downturn (performance shock). With the first kind of restriction, all the contemporaneous impacts of the restructuring program are entirely attributed to efficiency. In contrast, the contemporaneous effects from an economic downturn are not restricted. With the second kind of restriction, the economic downturn is restricted to have instantaneous effects on the performance only. At the same time the restructuring program may induce contemporaneous shifts on performance as well as on efficiency. Both restrictions have shortcomings which may bias the results: The first restriction ignores all instantaneous effects from efficiency on performance and the second restriction ignores the instantaneous effects from performance on efficiency. Since there is no theoretical hint about which bias is smaller we report IRF for both alternative restrictions and analyze whether the results depend on the choice of the restriction.

4 Data and Auxiliary Results

We source our raw data from the Deutsche Bundesbank. It includes balance sheet, profit and loss account as well as audit reports for all universal banks operating in Germany between 1993 and 2004. In addition, we have access to the default database

[15] As happened twice during this decade in East German areas on the banks of the river Elbe.

of the Bundesbank for most of these banks between 1995 and 2003. On this basis, we estimate efficiency and risk proxies, respectively.

4.1 SFA and efficiency

In line with the intermediation approach presented in section 3.1, we specify the volume of funds channeled to agents in the economy as bank output captured by interbank loans y_1, commercial loans y_2 and securities y_3. To account for the increasing importance of off-balance sheet (OBS) activities, we additionally follow Clark and Siems (2002) and specify OBS as a fourth output y_4. Subject to factor prices, banks demand three factors to produce this output portfolio: fixed assets, labor and borrowed funds. We approximate the price of fixed assets w_1 as depreciation over fixed assets.[16] Labor cost w_2 are calculated by dividing personnel expenses over full-time equivalent employees. The cost of borrowed funds w_3 is captured by the sum of interest expenses relative to interest-bearing liabilities, mostly deposits and bonds. Finally, we include the level of equity as a control variable z.

Tables 8 and 9 in the appendix depict parameter estimates of equation (1) and mean values and standard deviations of bank production and dependent variable data between 1993 and 2004, respectively. First, note that during the sample period the number of banks almost halved. As noted by Koetter et al. (2006), most of this consolidation is due to mergers and acquisitions rather than voluntary exits or outright failures. In fact, they show that higher inefficiency and lower performance increases the likelihood of distressed mergers. However, the interdependence of performance and efficiency as well as the dynamic effects over a longer forecast horizon remain unclear. Second, the importance to account for systematic differences between banks is underlined by large standard deviations of bank production data.[17]

At the bottom of table 9 we depict mean CE and PE estimates from the fixed effect panel frontier model. Frontier diagnostics, such as a significant ratio of systematic to random variance λ, support the specification of both cost and profit frontiers.[18] Mean CE is well in line with previous results reported for German, (Altunbas et al., 2001), European (Vander Vennet, 2002; Berger, 2003), or U.S. banking markets (Bauer et al., 1998).Our PE scores are somewhat lower compared to other European or U.S. studies (Amel et al., 2004), but similar to those that use comparable data sets and panel methods (Lang and Welzel, 1996; Koetter, 2006). Despite growing bank production, rising total costs and consolidating markets, CE is very stable over time. Apparently, relative performance was constantly monitored among German banks. On the other hand, PE exhibits a rather volatile time pattern in

[16] Mountain and Thomas (1999) criticize that most bank efficiency studies approximate theoretically exogenous factor prices with bank-specific expenditures. Here, we calculate input prices that banks face in regional markets (Koetter, 2006).

[17] One may argue that excessive heterogeneity requires the estimation of separate frontiers. However, comparing efficiency derived from different samples is not possible (Coelli et al., 2005). For example, 80% CE may be very good relative to one benchmark, but very poor in another peer group. Thus, we estimate a joint frontier and account for heterogeneity with bank-specific effects.

[18] Log-likelihood ratio tests also support the translog functional form with a time-trend.

table 9 while profitability continued to plummet since 1993.[19] Apparently, even in a period of steadily declining absolute profitability, the relative profit efficiency of banks differed considerably.

The apparent lack of correlation of both efficiency measures is well-documented in the literature (Bauer et al., 1998) and underlines our approach to analyze both efficiency measures' influences on profitability and risk. Simple descriptive statistics indicate to us that the long-term effects of shocks in the former are anything but clear ex ante and therefore call for the VAR approach chosen here. Beforehand, we turn to the estimation of our hazard model as to obtain risk proxies.

4.2 Hazard model and PD

To estimate the hazard model, we first have to define default events. While studies of U.S. banks can rely on fairly clear failure criteria (Cole and Gunther, 1995; DeYoung, 2003), most non-U.S. studies have to approximate failure on the basis of some financial ratio's threshold. In contrast to the latter, we can *observe* failures from the records of the supervisory authorities at the Bundesbank. The occurrence of six different events is recorded and classified as distress by the authorities. First, the announcement of situations that may indicate a restriction to the bank as a going concern according to §29(3) of the banking act. Second, a decline of the operating earnings ratio by more than 25%. Third, the announcement of losses in excess of 25% of liable capital. Fourth, capital injections by the respective pillars' insurance schemes. Fifth, a takeover serving restructuring purposes. Sixth, forced closure of the bank following a moratorium. Note, that the Bundesbank does not actively intervene in any of these events but merely records defaults since it does not have a legal mandate to, for example, close a bank or dismiss managers. Any legally binding interventions are conducted by the Federal Supervision Agency of Financial Services (*'Bundesanstalt für Finanzdienstleistungsaufsicht, BaFin'*). However, the Bundesbank conducts the ongoing supervision of banks and closely cooperates with the *Bafin*. Therefore, our definition of default is in line with supervisory policy in German banking and we can refrain from having to define some ultimately arbitrary threshold level of a financial ratio.[20]

Next, we select covariates to predict these failure events. We follow broadly the CAMELS taxonomy described in section 3.2 and amend bank-specific covariates to capture the health of the corporate sector and bank market structure of banks' regional markets. Our dataset does not contain variables that adequately measure liquidity and management skill.[21] We therefore restrict the analysis to the categories capitalization, asset quality, earnings and sensitivity to market risk. In total, our model contains nine variables. Since we specify lags for each covariate of two years to predict default events, our resulting sample contains 21,599 observations between

[19] Mean return relative to total outputs declined from 100 basis points in 1993 to just 50 basis points in 2004. Poor profitability trends apply to all banking pillars (Koetter et al., 2006).

[20] In contrast to, for example, U.S. banking markets, none of the banks in the sample fell below the legally required minimum capitalization levels (Koetter et al., 2006). Hence, approximating default on the basis of financial data alone seems inappropriate.

[21] The Principle II liquidity reports are not available for the entire period and the management quality of a bank could be assessed with qualitative information collected in on-site inspections.

1995 and 2003. Out of these, we observe 550 defaults. Using these data for failure events and explanatory variables, we estimate equations (3) and (4) as described in section 3. Parameter estimates and mean covariates for distressed and non-distressed observations are depicted in table 1. The former are highly significant and display the expected sign. The area under the ROC curve amounts to roughly 0.76 which indicates a good discriminatory power.

Table 1: Parameter estimates Hazard model and mean covariates

Variable		**Coefficients**			**Mean of x**	
		(1)	**(2)**	**(3)**	*non-distress*	*distress*
Equity ratio	c_1	-0.098***			6.0	5.7
Securities	a_1	-0.030***			22.9	19.0
Bad loans	a_2	0.015***			22.1	27.3
Operating result	e_1	-0.022***			30.5	14.1
Loan-loss provisions	e_2	0.003*			29.2	388.6
Stocks	s_1	0.035*			1.6	1.9
Fixed income	s_2	0.0218***			-22.0	-15.1
Corporate insolvency	INS	0.610***			0.8	0.8
Bank market share	MS	-0.013***			15.2	11.7
Profit efficiency	PE	-0.004	-0.013***		32.7	31.2
Cost efficiency	CE	0.006		-0.015**	69.9	69.3
Without efficiency:	χ^2	380.62***				
	ROC	0.760				
With PE:	χ^2	382.19***				
	ROC	0.760				
With CE:	χ^2	379.51***				
	ROC	0.759				
Efficiency only:	*Wald* χ^2		74.79***	69.69***		
	ROC		0.596	0.588		
Observations		21,599	21,599	21,599	21,049	550

Notes: Population average model estimated with GEE; Year-dummies included; Banks: 3,332; Observations: 21,599; ROC is the area under the Receiver Operating Characteristics-curve; *,**,*** denote significant at the 1,5 and 10 percent level. All variables measured in percent. c_1: Equity capital and undisclosed reserves to balance sheet total, a_1: Total securities to total assets, a_2: Provisioned loans and loans with increased risks to audited loans, e_1: Operating results to balance sheet total, e_2: Provisions to operating results, s_1: Stocks to balance sheet total, s_2: Fixed-rate liabilities less fixed-rate assets to balance sheet total, INS: Corporate insolvency ratio per district ('Kreis') MS: Total asset market share per district ('Kreis')

Consider the baseline results in column (1) of table 1 first. We measure capitalization c_1 with the equity capital ratio. Equity capital here also contains undisclosed reserves. The negative sign of the coefficient indicates that increasing equity capital *ceteris paribus* lowers risk. Asset quality is measured with the ratio of total securities[22] to all assets a_1 and the ratio of provisioned loans or loans with increased risk to the total of audited loans a_2. The negative impact of securities on PD can be explained with a lower risk of securities compared to other assets. The opposite applies to provisioned loans or loans with increased risk, which exhibits a positive coefficient in table 1. We capture the earnings situation with operating results divided by balance sheet total e_1 and the share of provisions of the operating results

[22]Including primarily money market and fixed income assets.

e_2. As expected, the former enter the model with a negative sign. Higher operating results *ceteris paribus* improve a bank's financial health. In turn the latter indicates increased risk as witnessed by a positive coefficient. Sensitivity to share price fluctuations is measured with the share of stocks to the balance sheet total s_1. The rationale for the positive sign of the coefficient is the positive correlation between the volume of stocks and the exposure to stock market price risk. The exposure to interest rate risk is captured by the net fixed interest rate liabilities s_2, which also is positively correlated to default. Both ratios are rather simple compared to the market risk indicators developed in recent years. However, more sophisticated ratios were not available for the whole sample and the whole set of banks. The first regional control variable is the corporate insolvency ratio per district (*'Kreis'*) INS. It controls for the quality of the regional asset market and is linked to credit risk. The second regional control variable is the mean market share per district. It accounts for market power and therefore may be linked to both market risk and credit risk. Both variables presumably have a significant influence on default because many German banks operate on regionally confined markets.

We also analyze the discriminatory power of efficiency. To this end we first add the variables cost and profit efficiency to the hazard model, respectively, as depicted in column (1) in the second panel of table 1. In both cases we find no significant relation.[23] But a hazard model with efficiency as the only covariate yields a significantly negative impacts of profit efficiency in (column 2) and cost efficiency (column 3). Hence, efficiency alone is a helpful predictor for defaults but the predictive information is completely contained in other financial ratios. This result underpins the endogeneity of a bank's PD, performance and economic indicators such as efficiency. While efficiency itself is significantly correlated with bank defaults, the eminent threat of default for the chosen prediction horizon can be retrieved more directly by alternative financial indicators. These, in turn, may in fact follow structural inefficiencies of a bank. This endogeneity between efficiency and other financial ratios thus supports our approach to use VAR-modeling and seems to be an appropriate way to gain insight into the dynamic relationship between efficiency and risk.

5 Results

We discuss first specification tests for the VAR model and present next our results regarding shocks and responses of efficiency and performance, respectively.

5.1 Specification

Lag order The first step in VAR-modeling is to determine the appropriate lag order J of the reduced form given in equations (5) and (6), respectively. Lutkepohl (2005) suggests to estimate models with different lag orders and then to choose the model with the highest lag order that passes the diagnostic tests. We estimate the reduced form with the Arellano-Bond-GMM (AB) estimator for the lag orders of $J = 1, ..., 4$ (Arellano and Bond, 1991) in table 2.

[23] Coefficient estimates for other covariates hardly changed, as did explanatory power depicted by ROC values in the bottom panels of table 1.

Table 2: Optimal lag order J for the reduced form VAR

	Lag J	**Arellano-Bond autocorrelation test**[1)] AR(1)	AR(2)	AR(3)	AR(4)	**Sargan** χ^2	**AIC**
Efficiency equations							
CE on Score and CE	1	-16.585***	2.961*			215.8***	-0.2
	2	-15.286***	1.121	0.921		198.0*	-100.0
	3	-13.609***	1.675	-0.306	-0.691	176.3	-179.7
	4	-12.521***	0.660	0.043	-0.386	155.2	-234.8
CE on ROA and CE	1	-16.919***	2.379*			127.9	-88.1
	2	-15.365***	1.593	0.349		115.8	-182.2
	3	-14.668***	2.923**	-0.975	-0.803	110.2	-245.8
	4	-13.122***	1.200	-0.770	0.066	115.7	-274.3
PE on Score and PE	1	-34.152***	2.736**			307.7***	91.7
	2	-32.976***	-1.292	1.522		252.4***	-45.6
	3	-30.085***	2.142*	-2.078*	1.183	216.5*	-139.5
	4	-27.279***	2.181*	-1.394	1.564	201.8	-188.2
PE on ROA and PE	1	-34.623***	2.101*			252.8***	36.8
	2	-33.832***	-2.207*	1.893		213.3***	-84.7
	3	-31.034***	1.232	0.268	0.773	185.6	-170.4
	4	-28.477***	2.977**	-2.639**	2.887**	160.2	-229.8
Performance equations							
Score on Score and CE	1	-2.935**	-0.705			543.7***	327.7
	2	-3.363***	2.927**	-1.398		310.7***	12.7
	3	-9.681***	2.525*	-0.362	1.951	235.1*	-120.9
	4	-10.219***	-0.905	-0.999	1.996*	199.7	-190.3
ROA on ROA and CE	1	-2.262*	-0.958			168.1***	-47.9
	2	-2.308*	1.327	-1.570		214.1***	-83.9
	3	0.967	0.858	0.311	-1.371	296.4***	-59.6
	4	1.023	0.304	0.073	-0.042	215.8	-174.2
Score on Score and PE	1	-3.020**	-0.650			532.6***	316.6
	2	-3.247**	2.820**	-1.345		307.8***	9.8
	3	-9.304***	2.970*	-0.456	1.950	271.6***	-84.4
	4	-10.188***	-0.606	-0.982	2.009*	235.5*	-154.5
ROA on ROA and PE	1	-2.285*	-0.957			183.6***	-32.4
	2	-2.289*	1.284	-1.586		192.9**	-105.1
	3	0.994	0.862	0.438	-1.300	229.8**	-126.2
	4	1.044	0.293	0.167	-0.116	135.3	-254.7

Notes: AB-GMM two-step estimation with time-dummies; *,**,*** significant at 5%, 1% and 0.1%. Degrees of freedom for Sargan test for lag order j=1,..,4: 108, 149, 178, 195, respectively.
[1)] (Arellano and Bond, 1991)

We report the AIC, the Sargan test of over-identifying restrictions and the Arellano-Bond tests of autocorrelation for the whole set of our variables.[24] We depict results from the efficiency equations in the upper panel and those from the performance equations in the bottom panel.

The AIC criteria unanimously advocate the maximum lag order of four. In most cases the Sargan test also turns insignificant for higher lag orders.[25] Therefore, we focus on the models with $J = 4$.[26] Table 2 shows that the residuals from the regression of PE on ROA and PE are autocorrelated. When reducing the model to smaller lag orders the autocorrelation seems to vanish. This is counterintuitive, since increasing lag orders should come along with reduced autocorrelation of the residuals. Potentially, this result is attributable to a loss of degrees of freedom. Except for

[24] We use the two-step estimator for regression diagnostics and the one-step estimator for inference about coefficients because t-ratios of the former estimator are unreliable (Bond, 2002).

[25] The only exception is the regression of $Score$ on $Score$ and PE. Tests for autocorrelation of higher order than four lags are infeasible due to sample size.

[26] Note that the AB estimator takes differences of the variables in equations (5) and (6). This introduces a first-order MA-component in the model. As a result, significant test statistics of first order autocorrelation do not indicate a misspecification.

three specifications all remaining 4^{th}-order models pass the autocorrelation test.[27] Overall the results confirm that the model with four lags is optimal.

Stationarity As noted in section 3.3, our approach of solving the reduced form to obtain the structural MA representation requires that the dependent variables are stationary. Therefore, we test all four measures for panel unit roots for one up to four lags. Since our panel is unbalanced we use an augmented Dicky Fuller test in the vein of Maddala and Wu (1999) rather than the Im-Pesaran-Shin test (2003). The according tests statistics are depicted in table 3.

Table 3: Fisher test for panel unit roots

		Efficiency		**Performance**	
Lag	**Statistic**	*CE*	*PE*	*Score*	*RoA*
1	χ^2	16,700	15,900	15,100	14,500
	p-value	0.000	0.000	0.000	0.000
2	χ^2	11,600	10,800	9,804	11,000
	p-value	0.000	0.000	0.000	0.000
3	χ^2	9,546	8,279	7,661	8,706
	p-value	0.000	0.000	0.000	0.000
4	χ^2	5,902	5,638	2,748	6,103
	p-value	0.000	0.000	0.000	0.000

Our results pertain that we can reject the hypothesis of non-stationarity for all four series. While this does not imply per se that resulting IRF are reasonable, stationarity is a necessary condition for our methodology. Consider therefore next the respective shocks and according responses of both efficiency and performance, respectively.

5.2 Shocks and responses

We calculate two separate Impulse Response Functions (IRF) for each efficiency-performance pairing depicted in figures 1 through 4, respectively. The first impact multiplier restriction (IMR) entails that the instantaneous impact multiplier of performance in the equation for efficiency is zero. The second IMR is that the instantaneous impact multiplier of efficiency in the equation of performance is zero. We also show 90%-confidence intervals for the IRF.[28] To ease interpretation, we further divide the coefficients in equation (9) by β_{110} and the coefficients in equation (10) by β_{220}. The transformed coefficients represent the response to unit shocks.[29] The

[27]The specifications *Score* on *Score* and *PE* and on *Score* and *CE* as well as *PE* on *Score* and *PE*, respectively, yield significant autocorrelation of higher order than one, albeit only at the 5% percent level.

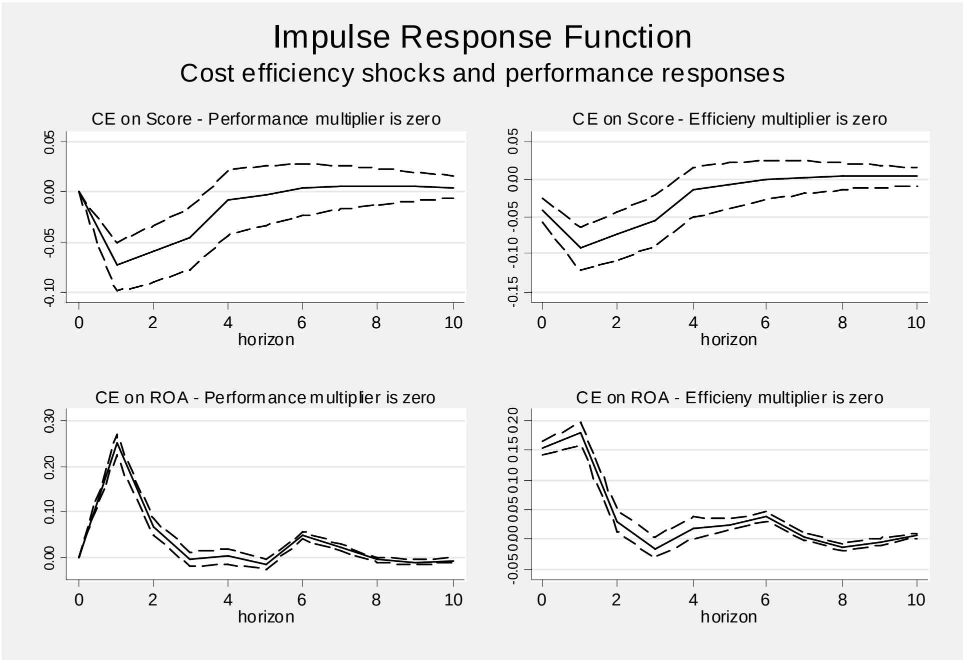
[28]For the calculation of the confidence intervals we randomly draw 1,000 sets of values for the coefficients in the VAR model with the estimated mean and standard error and calculate the IRF afterwards based on this model. The 90% confidence interval is then given by the 5% and 95% percentile of the simulated IRF distribution.

[29]We also calculated IRF on the basis of shocks of one standard error. Results are qualitatively not affected.

corresponding long-run multipliers (LRM) are reported for each of the four pairings investigated, too.[30]

Cost efficiency shocks We are most interested in the performance responses to shocks in efficiency. Consider to this end figure 1, which depicts the relations between CE shocks and both $Score$ and ROA responses, respectively.

Figure 1: Unit shocks in CE and performance responses



Regarding the dynamics of a CE shock on risk as measured by $Score$, consider the IRFs in the upper panel of figure 1. Independent of the chosen restriction, both exhibit large responses in the period after the occurrence of the shock. Afterwards the responses continuously and rapidly decay. Responses finally turn insignificant after about four periods. The empirical evidence therefore confirms the role of efficiency as an effective target when aiming at lowering a bank's risk. Our results for cost efficiency improvements thus support the view that the political objective of enhancing efficiency does not jeopardize the average riskiness of German banks. This is corroborated by odds ratios calculated from the long-run multipliers, which we report in table 4. For CE the odds ratio implies that a unit shock lowers the odds to default by about 10 to 20 percent. This underpins that targeting efficiency improvements can yield substantial and sustained reductions of risk.

Apart from reducing risk, a shock in CE furthermore improves bank profitability considerably as shown in the bottom panel of figure 1. Shocks reach their maximal impact approximately after one year, wear out very rapidly and do virtually not exist anymore after the second period. While the restriction choices lead to somewhat

[30]As noted earlier, long run multipliers are calculated on the basis of the estimated reduced form model. While the latter is ill-suited for direct inference due it's forecasting nature, we depict individual parameter estimates for completeness in table 10 in the appendix.

Table 4: Long run multipliers: Cost efficiency and performance

Shock in	Impulse on	IMR[1)] on	LRM[2)]	OR[3)]
CE	Score	CE	-0.253	0.777
CE	Score	Score	-0.155	0.856
CE	Profit	CE	0.436	
CE	Profit	Profit	0.369	

[1)] IMR: Instantaneous Multiplier Restriction; [2)] LRM: Long-run multiplier; [3)] OR: Odds Ratio equal to $OR = e^{LRM}$.

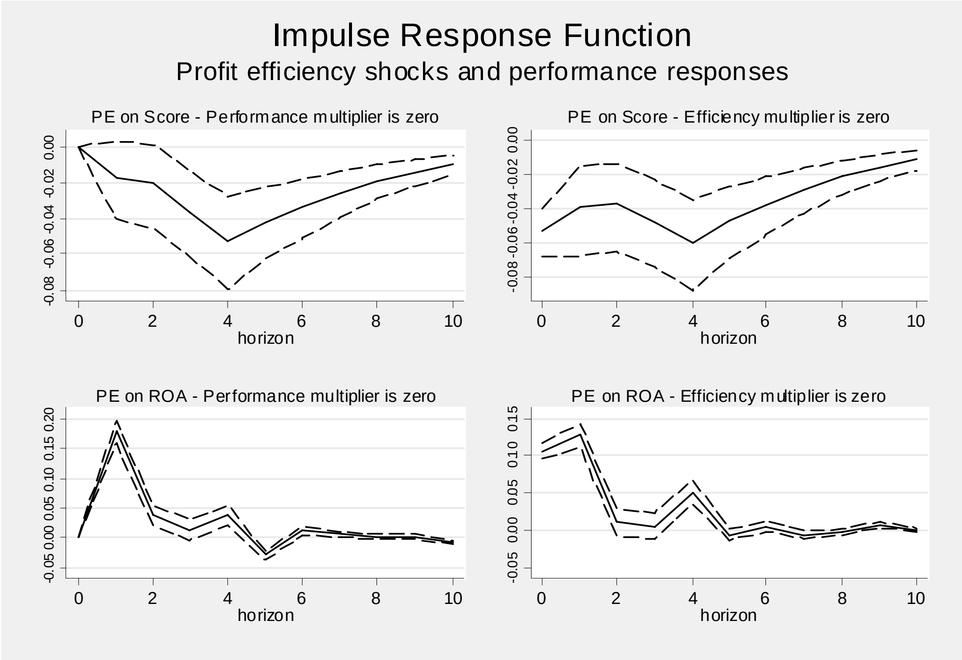
different evolution paths of ROA in the immediate aftermath of a CE shock, the short-run nature of effects is robust for both. The cumulative effects for shocks from cost efficiency are approximately 0.4. Thus, cost efficiency improvements lead to an immediate increase of profits but only to limited long-run effects.

In sum, both impulse-response functions and long-run multipliers show that in all periods where the responses are significantly different from zero, higher cost efficiency lowers risk and increases profits. The choice of restrictions seems to be of minor importance for most of our results as witnessed by similar long-run multipliers for the different restrictions reported in table 4.

Profit efficiency shocks A number of bank efficiency studies demonstrate that cost efficiency alone may not reflect the full picture of bank's ability to manage their business appropriately in competitive markets. European banking studies emphasizing the importance to analyze also profit efficiency are, for example, Altunbas et al. (2001) or Maudos et al. (2002). They argue that ongoing deregulation and increased competition from non-bank financial intermediaries necessitates not only efficient cost management. It is at least equally important to supply a vector of outputs in correct proportions. In the same vein, much of the legislative initiatives to create a level playing field in European banking aim especially at increasing profit efficiency in the sense of providing customers with the desired range of financial services at optimal prices. But, for example, the European Central Bank (2005) point out that such profit efficiency improvements imply increased pressure on margins, thereby reducing profits. Efforts to enhance efficiency may even induce excessive risk-taking in an attempt to defend market shares. To assess the consequences of a shock to PE consider figure 2.

Instantaneously, the impact of a shock in PE on risk is small and even declining during the first years. However, efficiency changes exhibit a high persistence and reach their maximum after four years. The long-run effect on score is about -0.4 (for the restriction on PE) and -0.3 (for the restriction on $Score$) according to our results shown in table 5. As for cost efficiency, we also report the odds ratios and find that a unit shock in PE lowers the odds to default by about 25 to 35 percent. Thus, profit efficiency has a larger impact on PD compared to cost efficiency. On the other hand, cost efficiency impacts immediately on PD while the effects from profit efficiency unfold completely only after four years. A possible policy implication from this finding is that cost efficiency is an appropriate target for banks that aim

Figure 2: Unit shocks for PE and performance responses



to reduce their risk immediately. In contrast, profit efficiency seems preferable for enhancing the long-run risk profile of a bank.

Table 5: Long run multipliers: Profit efficiency and performance

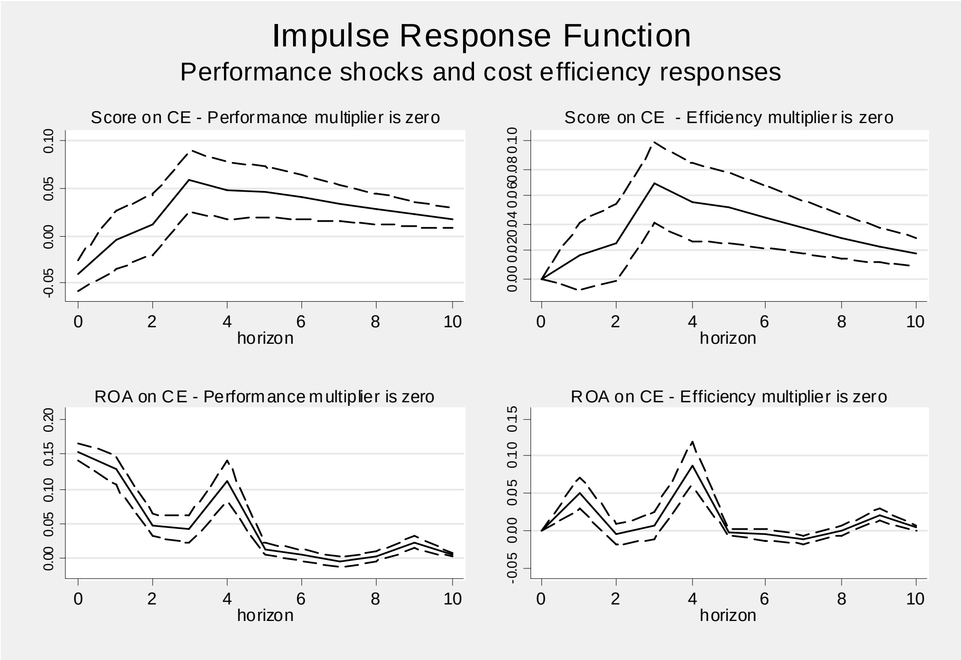
Shock in	Impulse on	IMR[1] on	LRM[2]	OR[3]
PE	Score	PE	-0.408	0.665
PE	Score	Score	-0.284	0.753
PE	Profit	PE	0.298	
PE	Profit	Profit	0.257	

[1] IMR: Instantaneous Multiplier Restriction; [2] LRM: Long-run multiplier; [3] OR: Odds Ratio equal to $OR = e^{LRM}$.

With respect to profitability, PE shocks mimic the dynamics of cost efficiency shocks. The effects on ROA reach their maximal impact after one year and vanish quickly in subsequent periods yielding an overall effect of 0.3. Thus, both types of efficiency improvements come along with an immediate increase of profits. The long-run effects from cost efficiency, however, are larger compared to profit efficiency.

Cost efficiency responses By means of examples we considered so far efficiency shocks, which may either emanate from macroeconomic or microeconomic changes. An example of the former are deregulation efforts such as the introduction of a single banking license in Europe. An example for the latter are restructuring programs or replacement of incumbent managers. However, we need to acknowledge that none of these examples is founded in theory. In fact, it is also perfectly conceivable that performance shocks occur and efficiency changes in response to that. Due to this lack of theoretical guidance, which exists in macroeconometric VAR applications, for example, by modeling monetary shocks, we also report results for cost and profit efficiency responses to performance shocks, respectively. In the top panel of figure 3 we depict to this end CE responses to a unit shock in $Score$.

Figure 3: Unit performance shocks and CE responses



In contrast to the reverse relation of shocks in CE and resulting $Score$ responses depicted earlier, our results show that a shock in risk actually increases CE significantly for up to ten years. While the dynamics differ slightly according to the choice of restriction (see right panel in figure 3), the bottom line remains qualitatively robust. This response of efficiency to shocks in $Score$ may reflect banks' efforts to change efficiency when performance is deteriorating. Increasing risk comes along with a long-run increase in cost efficiency, which peaks after approximately three years before the responses decline slowly thereafter. Apparently, banks focus on improving their ability to provide financial services cost efficiently after having experienced a shock in PD.

Table 6: Long run multipliers: Performance and cost efficiency

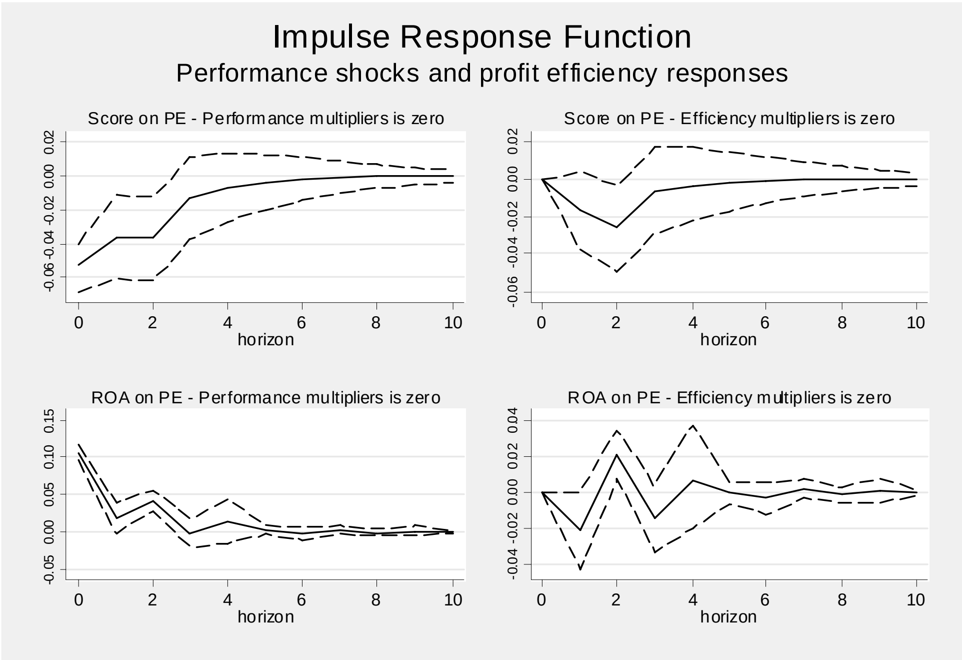
Shock in	Impulse on	IMR[1] on	LRM[2]
Score	CE	CE	0.398
Score	CE	Score	0.287
Profit	CE	CE	0.137
Profit	CE	Profit	0.522

[1]IMR: Instantaneous Multiplier Restriction; [2] LRM: Long-run multiplier; [3]OR: Odds Ratio equal to $OR = e^{LRM}$.

The response of CE on profitability shocks regarding both the shape of the impulse response functions and the magnitude of the long-run multipliers depicted in table 6 also differ across restriction choices. Short-run restrictions on efficiency lead to lower long-run multipliers (0.1 for CE) than short-run restrictions on profits (0.5 for CE). Robust to the short-run restriction is that in all cases the impacts on cost efficiency are positive, yet very volatile, and last around four years.

Profit efficiency responses As can be seen from figure 4, the reverse relation between *Score* and PE differs from the reverse relation with cost efficiency. Increasing risk has only small positive effects on profit efficiency. Impulse response functions for both multiplier restrictions yield mostly insignificant effects after two years. Hence, profit efficiency seems to be hardly affected by sudden changes in the risk profile of the bank.

Figure 4: Unit performance shocks and PE responses



The responses of efficiency on profitability shocks also depend on the choice of the restriction, as indicated by different shapes of the impulse response functions and the magnitude of the long-run multipliers. Short-run restrictions on efficiency lead to lower long-run multipliers (zero for PE and 0.1 for CE) than short-run restrictions on profits (0.2 for PE and 0.5 for CE). Robust to the short-run restriction is that in all cases the impacts on cost efficiency are higher than on profit efficiency and that the overall effect is positive. A positive impact from profit shocks on efficiency suggests that, in contrast to risk shocks, banks do not react to profitability shocks with efficiency enhancing measures. Potentially, these two dimensions of performance are regarded as substantially different problems that each require alternative management reactions.[31]

[31] For example, banks may indeed target efficiency after risk shocks but may try to acquire market power through mergers (Amel et al., 2004), or boost sales by entering new markets after a profitability shock (Berger et al., 2003).

Table 7: Long run multipliers: Performance and profit efficiency

Shock in	Impulse on	IMR[1] on	LRM[2]
Score	PE	PE	-0.051
Score	PE	Score	-0.150
Profit	PE	PE	-0.008
Profit	PE	Profit	0.182

[1]IMR: Instantaneous Multiplier Restriction; [2]LRM: Long-run multiplier; [3]OR: Odds Ratio equal to $OR = e^{LRM}$.

But given the volatile pattern of effects, their bare significance and the very low magnitude, we are more inclined to hypothesize that the relation between profitability shocks and efficiency reactions is simply weak. Perhaps the long-run nature of many efficiency enhancing measures, such as restructuring projects, is simply considered an inappropriate management tool to react to declining profits.

To sum up, our results confirm that efficiency is a powerful means to enhance a bank's performance. Both, cost and profit efficiency shocks increase profits and decrease risk. Cost efficiency impacts with a shorter time lag on probability of defaults than profit efficiency at the expense of a lower long-run effect. Cost efficiency, on the other hand, has a slightly larger overall effect on profits. By and large, results are robust to the different restrictions used in our estimation and only profitability shocks and responses exhibit alternative dynamics subject to this choice.

6 Conclusion

In this paper we suggest a VAR approach to model and quantify the intricate interrelations between bank efficiency, risk and profitability. While our approach is antithetic to recent theoretical developments of general equilibrium models, such as in Goodhart et al. (2006), we aim to contribute complementary agnostic evidence on the issue if efficiency gains and sustained performance are mutually exclusive objectives. In short, we find for the German banking market that both objectives do not contradict each other.

We use a sample of German universal banks between 1993 and 2004. On the one hand, we measure cost and profit efficiency (CE and PE) with stochastic frontier analysis. On the other, we approximate a bank's risk with a hazard model using historical distress data provided by the Deutsche Bundesbank. These measures are then employed to estimate a dynamic panel VAR. In line with theoretical predictions, we find indeed that efficiency and performance measures exhibit complex interdependencies. Both determine each other both contemporaneously and over time. To quantify the long-term dynamic effects of shocks in either of our measures, we calculate impulse response function for a forecast horizon of ten years. Our main findings are as follows.

First, we find that both kinds of efficiency improvements reduce risk and increase profitability. The largest cumulative long-term effects are those of PE shocks on risk and CE shocks on profitability. Consequently, bankers are well-advised to target efficiency improvements since they can yield sustained and pronounced improvements in profitability and risk.

Second, the dynamics of shocks and effects differ across our four efficiency and performance measures respectively. While CE improvements reduce the risk of a bank immediately, PE improvements fully unfold only after four years but impact for as long as up to 10 years. Thus, bankers and/or regulators that see need for immediate action to reduce a bank's probability of default may want to focus on cost efficiency. In turn, sustained risk reduction warrants a stronger focus on the bank's relative ability to maximize profits given its production plan.

Third, interactions between efficiency and performance are asymmetric. Higher efficiency reduces risk, but increases in risk lead to higher efficiency, especially on the cost side. This result suggests that bankers aim especially at cost efficiency improvements, for example by means of restructuring programs, after having experienced a risk shock. In turn, higher efficiency affects profitability positively and vice versa. Thus, bankers seem to react only to shocks in their riskiness by improving efficiency while profitability declines are according to our results no spark to launch efficiency improvements.

To our knowledge, our results provide for the first time empirical evidence about the dynamic interdependencies of efficiency and performance. The quantification of shocks and responses show that efficiency improvements are a useful target to improve profitability and reduce risk. Our findings suggest that efficiency enhancing measures, for example the promotion of more competition, do not bear immediate dangers of excessive risk-taking or sudden profitability distortions. Our results regarding different timing patterns of these effects may be of interest to policy makers and regulators as well as bankers and consumers of financial services alike.

Clearly, this research is at the same time subject to a number of limitations, which warrant future research. First, our model does not explicitly allow for contagion effects across banks. This is an important limitation when drawing inference for policy-making at the macroeconomic level. Second, the VAR methodology suggested here is completely a-theoretical. Future extensions should aim to follow the developments of macroeconomic VAR modelling and devise structural VARs. Specifically, augmenting the model for an explicit competition equation along the adjusted PR-approach of Bikker et al. (2006) seems challenging yet promising in this respect. Finally, our model does not account explicitly for (cross-border) bank market consolidation, which certainly is an important item on policy makers' agendas, too.

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7 Appendix

Table 8: Parameter estimates cost and profit frontier

Dependent	Cost		Profit	
Log-likelihood	-85,833		-39,813	
σ_u	9.71		2.52	
σ_v	0.30		0.11	
	β	p-value	β	p-value
lny_1	0.559	0.000	0.403	0.000
lny_2	-0.750	0.000	0.267	0.000
lny_3	0.695	0.000	0.370	0.000
lnw_1	0.613	0.000	0.246	0.000
lnw_2	-0.090	0.108	0.108	0.000
lnz	1.211	0.000	0.020	0.444
$0.5lnw_1w_1$	0.034	0.000	-0.013	0.000
$0.5lnw_1w_2$	-0.330	0.000	0.097	0.000
$0.5lnw_2w_2$	0.639	0.000	-0.080	0.000
$0.5lny_1y_1$	-0.001	0.487	0.037	0.000
$0.5lny_1y_2$	-0.083	0.000	-0.104	0.000
$0.5lny_1y_3$	-0.021	0.000	-0.030	0.000
$0.5lny_2y_2$	0.034	0.000	0.083	0.000
$0.5lny_2y_3$	-0.078	0.000	-0.029	0.000
$0.5lny_3y_3$	0.102	0.000	0.058	0.000
$0.5lnz$	-0.166	0.000	-0.011	0.002
lny_1w_1	0.016	0.000	-0.007	0.000
lny_1w_2	-0.037	0.000	-0.015	0.000
lny_2w_1	-0.109	0.000	-0.031	0.000
lny_2w_2	0.061	0.000	-0.027	0.000
lny_3w_1	0.056	0.000	0.023	0.000
lny_3w_2	-0.210	0.000	-0.074	0.000
lny_1z	0.031	0.000	0.024	0.000
lny_2z	0.108	0.000	-0.002	0.180
lny_3z	-0.057	0.000	-0.028	0.000
lnw_1z	0.034	0.000	0.002	0.321
lnw_2z	0.179	0.000	0.135	0.000
t	-0.054	0.000	-0.037	0.000
t^2	0.005	0.000	-0.001	0.000
lny_1t	0.005	0.000	-0.001	0.010
lny_2t	-0.007	0.000	0.005	0.000
lny_3t	0.015	0.000	0.001	0.001
lnw_1t	0.030	0.000	-0.005	0.000
lnw_2t	-0.036	0.000	0.024	0.000
$lnzt$	-0.012	0.000	-0.007	0.000
σ	9.715	0.000	2.521	0.000
λ	31.982	0.000	22.233	0.000

Notes: N: 34,191; K: 3,827

Table 9: Bank production data and efficiency 1993-2004

Year		1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	Total
Bank production														
y_1	Commercial loans	171	186	220	261	305	359	423	513	578	644	679	730	382
		1,760	1,970	2,300	2,790	3,360	3,970	4,740	5,590	6,150	6,390	6,720	7,340	4,440
y_2	Interbank loans	380	421	471	538	608	695	838	1,020	1,150	1,220	1,270	1,310	757
		3,200	3,390	3,880	4,520	5,350	6,490	7,360	9,110	10,000	9,670	9,810	10,500	6,920
y_3	Securities	138	164	182	215	259	313	412	517	603	623	708	796	365
		894	1,040	1,250	1,580	2,160	2,870	4,010	4,900	5,670	5,330	6,610	7,950	3,900
y_4	OBS	95	105	121	144	179	205	261	312	370	363	355	359	218
		1,360	1,460	1,640	1,940	2,360	2,800	3,550	4,190	4,900	4,340	3,980	4,100	3,060
w_1	Price of fixed assets	24.7	25.9	24.7	45.6	18.9	16.2	16.6	15.6	15.9	16.5	25.3	25.6	23.2
		229.4	356.2	417.0	1315.4	150.6	13.0	57.5	13.9	16.1	29.4	319.8	337.8	469.4
w_2	Price of labor	40.2	43.8	46.7	47.8	50.3	57.5	52.5	54.7	63.7	56.7	59.4	59.6	51.5
		11.9	10.9	21.5	13.4	49.7	374.1	17.9	21.6	381.1	19.2	20.7	15.5	151.3
w_3	Price of funds	5.0	4.3	4.2	3.8	3.6	4.0	3.4	3.5	3.5	3.2	5.1	2.8	3.9
		1.0	1.2	1.9	1.5	0.9	16.7	5.8	0.9	0.7	0.8	101.4	11.4	25.5
z	Equity	28.4	33.5	37.2	40.6	46	52.8	63	76.1	88	99.6	100	102	58.4
		241	276	306	326	382	467	555	673	751	774	688	659	507
TOC	Cost	51.8	52.1	56.2	60	66.6	77.6	90.8	121	136	127	123	122	84
		413	405	442	488	566	706	838	1170	1260	1000	943	925	767
PBT	Profit	7.4	8.3	7.9	8.7	9.3	9.9	10.6	11.5	11	13.8	14.9	15.8	10.2
		65.9	54	48.1	53.3	60.8	72.7	65.9	72.6	65.5	102	73.9	78.6	67.1
Bank efficiency														
CE	Cost efficiency	70.7	69.4	69.8	69.5	69.8	70.4	69.8	68.4	69.7	69.6	69.3	69.3	69.7
		5.6	5.8	5.7	5.5	5.4	5.7	5.9	6.2	6.3	6.1	6.1	6.9	5.9
PE	Profit efficiency	29.2	36.3	32.9	34.9	34.8	30.4	34.3	28.6	24.6	29.6	32.8	35.0	32.1
		10.1	9.6	9.6	10.0	9.8	9.5	10.2	10.5	9.1	9.8	10.7	10.8	10.5
N	Banks	3,681	3,562	3,454	3,333	3,226	3,050	2,803	2,548	2,338	2,180	2,045	1,971	34,191

Notes: Outputs, equity, operating cost and profit measured in millions of Euro; Price of fixed assets and funds in percent; Price of labor in thousands of Euro. First line denotes mean values, second line denotes standard deviations.

Table 10: Parameter estimates reduced form VAR

		Efficiency				Performance			
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent		CE	CE	PE	PE	Score	ROA	Score	ROA
$\beta^{1)}$	**Lag**								
CE	1	0.521***	0.496***			-0.008***	0.243***		
CE	2	0.100***	0.087***			0.001	0.066***		
CE	3	0.030**	0.014			0.001	0.036***		
CE	4	-0.001	-0.022*			0.003**	0.046***		
PE	1			0.368***	0.370***			-0.001	0.076***
PE	2			0.067***	0.059***			0	0.026***
PE	3			0.032***	0.026**			-0.001*	0.027***
PE	4			-0.003	-0.013			-0.001*	0.035***
Score	1	0.162		-0.351		0.413***		0.408***	
Score	2	0.102		-0.287		0.154***		0.149***	
Score	3	0.430***		0.32		0.022*		0.015	
Score	4	-0.094*		0.067		0.005		0.002	
ROA	1		0.054***		-0.049		-0.496***		-0.497***
ROA	2		-0.005		0.043*		-0.510***		-0.499***
ROA	3		0.016		-0.04		-0.446***		-0.452***
ROA	4		0.099***		0.016		-0.280***		-0.269***
Diagnostics$^{2)}$									
AR	1	-12.521***	-13.122***	-27.279***	-28.477***	-10.219***	1.023	-10.188***	1.044
AR	2	0.66	1.2	2.181*	2.977**	-0.905	0.304	-0.606	0.293
AR	3	0.043	-0.77	-1.394	-2.639**	-0.999	0.073	-0.982	0.167
AR	4	-0.386	0.066	1.564	2.887**	1.996*	-0.042	2.009*	-0.116
Sargan		155.20	115.73	201.79	160.24	199.68	215.75	235.5*	135.26
AIC		-234.80	-274.27	-188.21	-229.76	-190.32	-174.25	-154.47	-254.74

1) One-step AB-GMM estimation; 1) Two-step AB-GMM estimation.

Notes: Year-dummies included; *(**, ***) significant at a 5% (1%, 0.1%) level

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