Banking Performance in Euroland. Efficiency and the Impact of Strategic Variables: 2003-2012

Project Report

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Current ECB regulation emphasizes the viability of the banking industry and its agents in order to guarantee long-term the mechanics of the financial system. It is barely about scope and quality of the essential services rendered to the economy by banks in their role as financial intermediaries. This study puts these services and the systemic performance of banks at the center of a scientific debate. We use a non-parametric approach (Data Envelopment Analysis) to reveal the efficiency of 70 European banks significant under SSM-regulation and a Malmquist productivity index to track efficiency scores over 10 consecutive years. We are in particular interested to what extent the financial crises shows in the data and - employing panel regression models - try to identify which (macro) economic environment has positive effects on the systemic performance of banks.

Contents

1. Introduction

Over the last decade the reputation of banks and financial institutions as a whole has suffered severely. At least in the public eye the classical business model of the banking industry had got skewed already years before the break out of the current financial crises, with the building up of non-sustainable risk structures. Particularly the events of 2007 and 2008, the crises of markets for short-time debt (see Gorton and Metrick [2012]) with its effects on liquidity supply to banks, the repercussions throughout the global financial system and - consequently - the real side of the economy, have raised questions as to what extent banks play their assigned role as efficient market intermediaries.

Concerns over banks' performance in their capacity as financial intermediaries have put significant pressure on the industry to reform and consolidate. Fueled initially by liberalization of financial markets the process has somewhat accelerated in the course of the still pending crises of the global financial system, first and foremost due to a rigorous sector regulation. Its main piece, the Basel Accords, is based on more restrictive capital and liquidity requirements for financial institutions, essentially aiming at strengthening the capacity of the individual units to bear the risks taken. Consequently, the stability of the financial system, the central regulatory aim, is more or less defined by the capability of banks to survive critical states of the system itself; it is not, at least not primarily, a question of quality of conduct, meaning the conduct of banks in their role as transmission belt between funds and assets, and therefore as the ultimate catalyst of economic activity.

In our study we specifically try to explore the quality aspect of systemic bank performance, i.e. the bank's efficiency as a financial intermediary providing fundamental service to the economic system. Here, the stability of the financial system is directly linked to the industry's service dimension and the productivity of its units in sustainably facilitating the real side of the economy. In this context, risk and capital also play a vital role to the extent that they are key resources to the banking industry in providing the intermediary financial services. Stability of the financial system, in our sense, is therefore guaranteed by the (near) absence of inefficiencies on the side of the individual banks in employing these resources to meet socially preferred ends. These ends largely coincide with the essential functions of banks, such as maturity transformation and liquidity production, or the amelioration of informational asymmetries in the market. They play a key role in our assessment of the systemic performance of banks.

The structure of this report is as follows. Section 2 is concerned with the evaluation of the systemic efficiencies of the banks considered. These efficiencies are defined through a non-parametric measure employing Data Envelopment Analysis (DEA). We describe the input and output variables used in our assessment of bank performance and set forth the specifics of the selected DEA model. We track cross-period performance on the basis of a Malmquist (total factor) productivity index. Section 3 contains a short empirical analysis of bank related indicators and the DEA efficiencies. In particular we discuss the impact of the financial crisis on these indicators. In section 4 we estimate (regression) models relating the Malmquist index to macro economic variables. The main goal here is to find statistically robust relations and therefore the main tool here is an extreme bounds analysis. A short summary and some conclusions make up section 5.

2. Performance Measurement and the Banking Industry

The performance of the banking sector is crucial for the long term stability of financial systems and subsequently for the efficient allocation of resources within our global economy. There are many valuable uses of performance analysis for bank management and policy makers alike, although in practice we might find cases of misperception of the performance concept itself. Whereas key financial indicators are commonly taken as an adequate measure of bank performance the underlying quality of employment of resources cannot be traced within established indicator systems. Therefore important economic issues such as productivity and efficiency respectively have long been tackled unsystematically by the sector for the price of loss of information and opportunity. Economic research on the other hand has embraced the subject and - over the last decades - produced a rich body of work employing different mathematical and econometrical models, and a great variety of data structuring techniques in order to provide new insights. For an overview of the relevant methodology regarding performance measurement or, more specifically, parametric and non-parametric approaches to performance measurement see e.g. Paradi and Zhu [2013].

One (non-parametric) approach to performance measurement, Data Envelopment Analysis (DEA), has attracted significant attention from economic research over the years. Since the publication of the seminal work of Charnes et al. [1978] on the subject of efficiency measurement in the case of multiple inputs and outputs, using mathematical programming and developing further the idea of a distance function relative to an efficiency frontier pioneered by Shephard [1953] and Farrell [1957], the scientific debate has broadened dramatically. It has produced a wide spectrum of alternative models and procedures to tackle practical economic problems concerned with relative productivity and efficiency (see e.g. Ray [2004], Cook and Seiford [2009] or Liu et al. [2013]).

DEA is a powerful tool when it comes to evaluating economic behavior. Offering a great variety of models with different specifications (see e.g. Ray [2004] or Cooper et al. [2007]) it can be adjusted to help solving various analytical problems, ranging from the decomposition of efficiency (see e.g. Camanho and Dyson [2005]) to the interpretation of scale effects including the definition of optimal production levels (see e.g. Banker et al. [2004]), and from the handling of fuzzy or imprecise data (see e.g. Cooper et al. [1999]) to the integration of strategic considerations (see e.g. Joro and Viitala [2004] or Bernroider and Stix [2007]) and of the concept of stochasticity into model design (e.g. Post [2001]). As far as applications of DEA in the banking sector are concerned we have seen quite an array of these extensions of the original approach to cover many important aspects of the industry, and at the same time build a strong basis for effective management action and economic policy measures.

2.1. The DEA Approach to Total Factor Productivity

This study involves a performance assessment in a multiinput-multioutput setting comparing a set of ECB-defined system-relevant banks in the Euro-Zone with respect to systemic efficiency based on their intermediary role on financial markets. In this context, Data Envelopment Analysis allows us to establish the (in)efficiency status of banks (Decision Making Units or DMUs) based on the concept of an efficiency frontier (production function in $\mathbb{R}^m$) and the position of the banks´ realized m-dimensional performance vectors relative to that frontier. DEA uses linear programming in order to identify deviations from efficiency status and the respective adjustment needs on the level of the individual units. Here, constrained optimization (the objective function always depending on the layout of the specific DEA model employed) serves us in defining the relevant dominant peers for every bank and to derive (via linear combination of the dominant performance vectors) benchmarks for underperformers.

The DEA model employed integrates 6 performance dimensions which establish the production model we use in the assessment of the (systemic) efficiency of banks: level of banking activity, risk taking, liquidity demand, market intelligence, liquidity production and capital endowment. On the "input side" of our model there are three variables: (1) Total Assets (TA): we use the (on-balance sheet) data as a proxi for the activity level of the individual units and as the basic discriminatory variable in our set of banks; (2) Risky Assets (RA) as a portion of Total Assets (RA.TA): Here, Risky Assets (not risk structured) stand for the risk load of the bank´s business (on-balance-sheet data) and is made up by the residual of total assets when eliminating positions with little or no risk potential such as Cash and Cash Equivalents (e.g. titels eligible for refinancing with central banks), and all debt securities issued by governmental institutions; and (3) Liabilities to Banks in Relation to Total Assets (LtB.TA): we employ this specific interbank debt ratio to illustrate the degree of leveraging through interbank borrowing. The figure will also serve us as a proxi of the potential liquidity stress in the case of bank runs in the money markets (which today seem much more likely than the traditional sort). The "output side" of our model is also made up by three key variables: (1) Liquidity Production (LP): here we combine the banks´ loans and receivables (private customers and financial institutions) with their holdings of debt securities. The aggregate stands for the eventual provision of liquidity to the real side of the economy; (2) Information Production (IP): The screening function of banks is a very important element to the efficient allocation of resources throughout the economy. We use an indirect measure to get a grip on the respective performance of banks. (Varying) annual allowances and direct write-downs in the loan category are interpreted as special depreciations of parts of the initially (at the time of the grant of the loan) unimpaired stock of trust in the bank´s market intelligence function. We set the income statement relevant and sustainable devaluations of loans (no netting), both to customers and banks, in relation to the aggregate loans at the beginning of individual period analyzed; (3) Stability Index (SI): Here, we try to explore the sustainablity of the banks´ capital. In that context, the leverage ratio Equity (Eq) to Risky Assets (RA) serves as a proxi fort he contribution of the individual unit to (some kind of technical) stability of the financial system which is at the center of the Basel Accords.

In our assessment of the systemic performance of banks we opt for a (6-dimensional) slack-based efficiency measure (SBM), non-orientated, allowing for variable returns to scale. This way we secure "strong", more realistic efficiency scores. Further, we introduce into our SBM-Model the concept of "super-efficiency" which will help us to increase the discriminatory power of the model and get more information on the efficient banks´productivity growth over time.

This concept of super-efficiency based on a slack based measure is described in Tone [2002]. Suppose we have given n banks with 3 input variables x_{ij} and 3 output variables y_{ij} where $i = 1, \ldots, 3$ and $j = 1, \ldots, n$ is an index for the bank. The slack-based efficiency measure (SBM) for the k-th bank is obtained by solving the following fractional program

$$\rho_k^* = \min \rho \qquad \rho = \frac{1 - \frac{1}{3}\sum_{i=1}^{3} s_i^- / x_{ik}}{1 + \frac{1}{3}\sum_{i=1}^{3} s_i^+ / y_{ik}}$$

$$\begin{aligned}
\text{subject to} \qquad & x_{ik} = \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- \\
& y_{ik} = \sum_{j=1}^{n} y_{ij}\lambda_j - s_i^+ \\
& s_i^- \geq 0,\ s_i^+ \geq 0 \\
& \sum_{j=1}^{n} \lambda_j = 1 \ \text{ and } \lambda_j \geq 0
\end{aligned}$$

The s_i^- and s_i^+ indicate the *input excess* and the *output shortfall* of the DMU under consideration and are also called *slacks*. The SBM-efficiency ρ_k^* satisfies $0 \leq \rho_k^* \leq 1$ and the DMU (bank) is called *SBM-efficient* if $\rho_k^* = 1$ holds (which is equivalent to zero slacks). For *SBM-efficient* DMUs in a second step the following fractional program is solved

$$\delta_k^* = \min \delta \qquad \delta = \frac{\frac{1}{3}\sum_{i=1}^{3} \bar{x}_i / x_{ik}}{\frac{1}{3}\sum_{i=1}^{3} \bar{y}_i / y_{ik}}$$

$$\begin{aligned}
\text{subject to} \qquad & \bar{x}_i \geq \sum_{j \neq k} x_{ij}\lambda_j \\
& \bar{y}_i \leq \sum_{j \neq k} y_{ij}\lambda_j \\
& \bar{x}_i \geq x_{ik},\ 0 \leq \bar{y}_i \leq y_{ik} \\
& \sum_{j \neq k} \lambda_j = 1 \ \text{ and } \lambda_j \geq 0
\end{aligned}$$

The optimum satisfies $1 \leq \delta_k^*$. If $\delta_k^* > 1$ holds then the DMU remains SBM-efficient even under (small) perturbations whereas for $\delta_k^* = 1$ arbitrarily small perturbations of the inputs/outputs may make the unit non efficient. Finally the super slack based efficiency score (SSBM) for a bank is defined as

$$\theta_k = \begin{cases} \rho_k^* & \text{if } \rho_k^* < 1 \\ \delta_k^* & \text{if } \rho_k^* = 1 \end{cases}$$

In fact, tracking the performance of individual units and the industry between 2003 and 2012 is one of the key aspects of this study. In that, we analyse the development of total factor productivity in the respective period using the Malmquist Index as a basis.

2.2. The Malmquist-Index

The Malmquist index (MI) was originally developed for the use in consumption analysis, some 60 years ago (Malmquist [1953]). Today, the index has become an important measure for productivity growth over time. It was first defined in the context of production theory by Caves et al. [1982] and first applied to a non-parametric setting by Färe et al. [1985]. There are several ways of calculating the Malmquist (productivity) index, one is through the use of multi-period DEA scores.

Modern Malmquist Index is a total productivity measure which can be composed by bringing together two major productivity growth aspects, the so called "Catch-Up" of the units under evaluation, meaning the improvement of the individual DEA efficiency scores over time, and the so-called "Frontier Shift", defining the cross-period movement of the very section of the efficiency frontier relevant for the unit assessed (MI = Catch Up x Frontier Shift). This study will use the DEA model outlined above to calculate the MI values for the years 2003 to 2012 and put them in context to the inter-temporal behavior of defined exogenous variables.

The SSBM efficiency $\theta_k(t)$ of the k-th bank in the year t is a function $\theta(\mathbf{z}_k(t), \mathbf{Z}_k(t))$ of the input/output factors $\mathbf{z}_k(t)$ of the k-th bank and the input/output factors of all the other banks $\mathbf{Z}_k(t)$ in the year t. The Malmquist index of the k-th bank (from year $(t-1)$ to year t) is defined as

$$\mathrm{MI}_k(t) = \left(\frac{\theta(\mathbf{z}_k(t), \mathbf{Z}_k(t-1))}{\theta(\mathbf{z}_k(t-1), \mathbf{Z}_k(t-1))} \frac{\theta(\mathbf{z}_k(t), \mathbf{Z}_k(t))}{\theta(\mathbf{z}_k(t-1), \mathbf{Z}_k(t))} \right)^{0.5}$$

Here e.g. $\theta(\mathbf{z}_k(t), \mathbf{Z}_k(t-1))$ is the SSBM score for the k-th bank if one uses the input/output factors of the bank at time t and the input/output factors of the other banks at time (t-1). The first factor of this expression reflects the change of the efficiency of the k-th bank under the assumption that the other banks don't "move" but stay at their "positions" of the year $(t-1)$. The second factor is quite analogous but here the input/output values of the other banks in the year t are used. This index may be factorized as

$$\mathrm{MI}_k(t) = \mathrm{CU}_k(t)\mathrm{FS}_k(t)$$

where

$$\mathrm{CU}_k(t) = \frac{\theta(\mathbf{z}_k(t), \mathbf{Z}_k(t))}{\theta(\mathbf{z}_k(t-1), \mathbf{Z}_k(t-1))}$$

is the so called *catch up (CU)* and

$$\mathrm{FS}_k(t) = \left(\frac{\theta(\mathbf{z}_k(t-1), \mathbf{Z}_k(t-1))}{\theta(\mathbf{z}_k(t-1), \mathbf{Z}_k(t))} \frac{\theta(\mathbf{z}_k(t), \mathbf{Z}_k(t-1))}{\theta(\mathbf{z}_k(t), \mathbf{Z}_k(t))} \right)^{0.5}$$

is the *frontier shift (FS)* which in a certain sense describes the movement of the part of the efficiency frontier which is relevant for the k-th unit.

2.3. The Sample

In this study we assess, for 70 European banks, the systemic efficiency as defined in the introductory section. These banks were among 128 listed as significant credit institutions under the regulation of the Single Supervisory Mechanism (SSM) in the Euro-Zone when the ECB published a provisionary list of banks in October 2013 to undergo a first screening process, in order to provide " (...) the necessary clarity on the banks that will be subject to the ECB´s direct supervision" (ECB [2013]). To be on that list the banks had to hold assets worth more than 30 billions Euros or more than 20% of their home country´s GDP. The institutions identified, which accounted roughly for 85% of the Euro-Zone´s bank assets, had to undergo an in depth examination in 2014 concerning risk structure, asset quality and liquidity. In the course of data compilation we have reduced the set of 128 banks significantly, eliminating institutions specialized in the real estate sector or the financing of the public sector. We have also not considered banks which serve as a finance vehicle for some of the biggest players in the global insurance market (and which are usually insignificant in size). And, of course, there have been cases, though only few, were information could not be retrieved. For the residual banks we have fully collected specified balance sheet and income sheet data for the years 2003 to 2012 using direct sources at the respective credit institution or drawing on official financial reporting (some 9.100 data points). We have exclusively build on consolidated financial data, whereby for the years 2006 and later we have in general used data according to the IFRS accounting standards; before 2006 we have relied on local accounting standards. Also, some few institutions significant to the ECB and part of our list have not yet opted for IFRS but have remained in their traditional accounting regime (e.g. german HGB). We know about the problems regarding aggregation and comparability which might potentially arise by this lack of inter-bank congruence of accounting. In this, we can assure the reader of our efforts to establish the best quality long range panel data possible.

Further details may be found in the tables table A.1 and table A.3.

3. Empirical Analysis

In this section we give a short description of the development of the banking variables considered through the years 2003-2012. These variables are listed in table A.1 and some key statistics may found in table A.4 and table A.5. Furthermore the results of the DEA analysis are inspected.

We start with a discussion of the (annual) growth rates of *total assets (TA)*, see figure 3.1 and table A.5. In the years before the crisis (2003-2007) the banking sector showed an enormous growth with median growth rates above 10%. In particular in 2005 the median growth rate was 17.9%. The median annualized cumulated growth rate from 2003 to 2007 was 15% and approximately 36% of the banks at least doubled their size (in terms of TA) during these 4 years. Only 2 of the banks considered have reduced their TA in this period. The picture changes completely during and after the crisis (2008-2012) where the median annual growth rates dropped to values slightly above 0% and about 46% of the banks shrunk (in terms of TA). The variation between the banks is huge and there are some extreme (upward) outliers[1]. E.g. in the years (2003-2007) *ABLV Bank* had an annualized cumulated growth rate of 44.6% and even during the crisis (2008-2012) *ABLV Bank* managed to grow by 21.6%.

In the year 2008 the growth has slowed down a little bit. Furthermore some of the other banking variables already indicate the start of the crisis, e.g. Eq, DeVAL, CoB, SI and IP. This is the reason, why we report the annualized growth rates for the period 2003-2007 and 2008-2012 in table A.5.

The *customer loans (CL), risky assets (RA)* and *liquidity production (LP)* behaved very similar to the total assets, see figure 3.1 and table A.5. The median annualized cumulated growth rates of the customer loans dropped from 15.7% (2003-2007) to 0.9% (2008-2012). Similar to total assets also these variables have some extreme outliers. E.g. *ABLV Bank* increased the customer loans before the crisis (2003-2007) by 80.5% per year and *La Banque Postale* expanded by 14.8% per year during and after the crisis (2008-2012). Risky assets and customer loans account for a large proportion of total assets and liquidity production respectively[2]. Therefore it is not surprising that risky assets and liquidity production behave very similar to total assets and customer loans respectively.

The *ratio of risky assets to total assets (RA.TA)* grows until 2008 and then decreases. The median annual growth rates of this ratio are positive until 2008 and then negative for the subsequent years. In particular the decrease in 2009 and 2012 is highly significant as is shown in figure 3.3. The median value of this ratio declined from 91% in 2003 to 87% in 2012 with a peak value of 94% in 2006.

The *interbank debt ratio (LtB.TA=LtB/TA)* steadily decreases from 19% in 2003 to 12% in 2010 and then jumps to 15% for 2011 and 2012. Figure 3.3 shows that the median growth rates of the interbank debt ratio are negative for all years except for 2005 and 2011.

The ratio *(CoB.TA=CoB/TA)* decreases from 11% in 2003 to 6% in 2012. In particular in 2008 and 2010 the median growth rate of *CoB.TA* is significantly negative, see figure 3.3.

The (median) annual growth rates of the *stability index (SI)* are close to zero before the crisis. The growth rate is significantly negative in 2008 (probably due to necessary value adjustments) and significantly positive in the years 2009 and 2012 (probably due

[1]Most of these upward outliers may be explained by merging and acquisition activities.

[2]The median ratio of risky assets to total assets is 91% and the median ratio of customer loans to liquidity production is 66%.

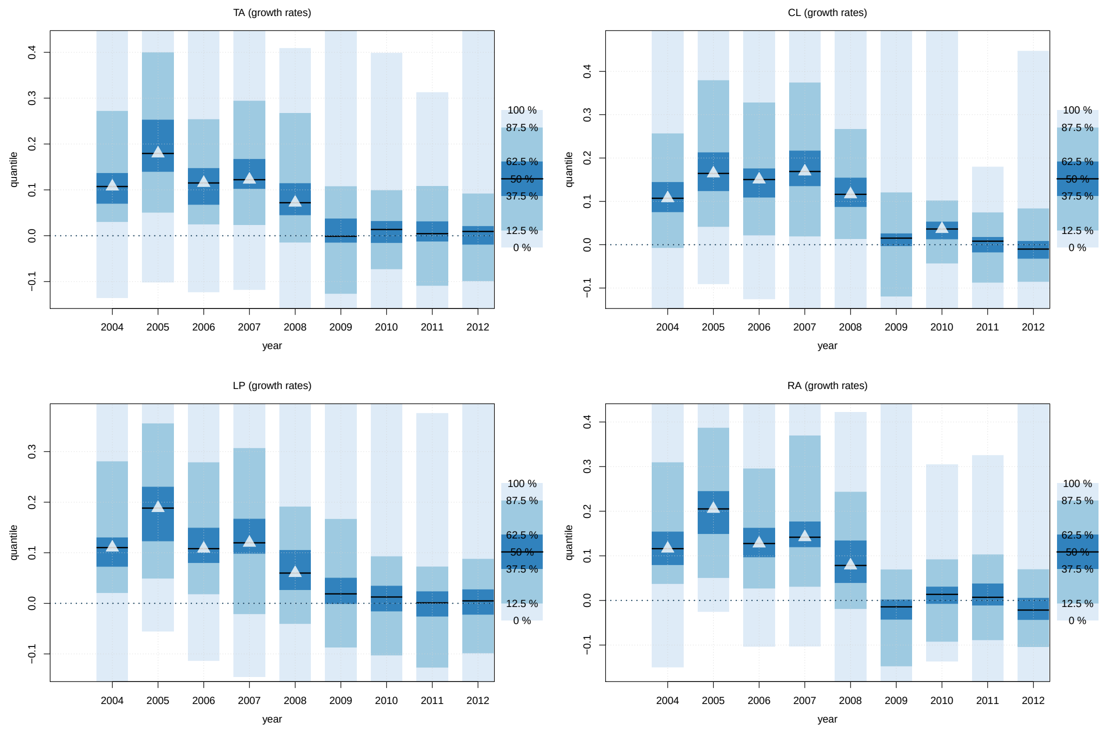

Figure 3.1: Quantile plot for the annual growth rate of total assets (TA), customer loans (CL), liquidity production (LP) and risky assets (RA). The plots show the movement of the quantiles (min=$q_{.0}$, $q_{.125}$, $q_{.375}$, median=$q_{.5}$, $q_{.625}$, $q_{.875}$, max=q_1) from 2004 to 2012. For each year a two sided binomial test is performed to test whether the median value is zero. If the median is significant (with a p-value less then 1%) and positive then this year is marked with an upward triangle. Correspondingly a down ward triangle marks a significant negative median.

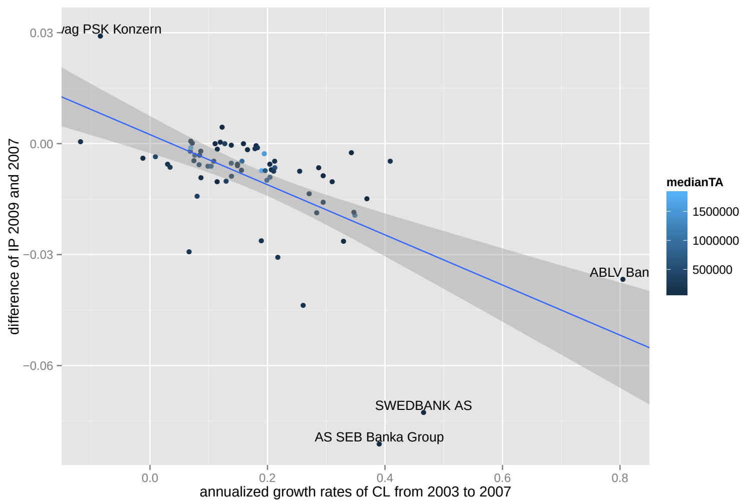

Figure 3.2: Scatterplot of the difference of the information production (IP) in the years 2009 and 2007 versus the annualized growth rate of the customers loans (CL) from 2003 to 2007. The color of the points codes the size of the banks (in terms of the median TA values).

to increased requirements on the equity ratios). However, the overall change during the considered ten years is rather small (the median stability index is about 6.5% in 2003 and 2012). Also other quantiles only show very small changes.

The annual growth rates of the relative devaluations of loans *(DeVAL.TA)* are (significantly) positive in 2008 and 2009, see figure 3.3.

The *information production (IP)* slightly increases before the crisis (only the median growth rate in 2004 is significantly positive) and then shrinks (significantly) in 2008 and 2009. In the following years the situation is somewhat relaxed with small (non significant) changes. In the years from 2003 to 2012 about 83% of the considered banks decreased their information production. However the median annualized growth rate for 2003 to 2012 is about -0.04% (i.e. pretty close to zero). The annualized cumulated growth rates are severely left skewed (The 12.5% quantile is -0.30% and the 87.5% quantile is 0.01%), i.e. the losses in IP are larger (in absolute values) than the increases. The inter quartile range of IP rises from 0.006 in 2003 to 0.020 in 2013, i.e. the variation of the banks with respect to IP increases.

The extreme growth of the banks (in terms of total assets as well as in term of customer loans) before the crisis was at least partly 'bought' by an increasing risk. A regression of the difference of the information production in 2009 and 2007 onto the annualized growth rate of customer loans from 2003 to 2007 gives a highly significant result. See figure 3.2.

The DEA efficiencies may be seen in figure 3.4. The median values of SSBM vary between 0.58 to 0.76 with the exception of 2007 with a median value equal to 1 and 2008 where the median is 0.87. That the years 2007/2008 are quite distinct from the others may also be seen in figure 3.5 where the empirical distributions of the DEA efficiencies

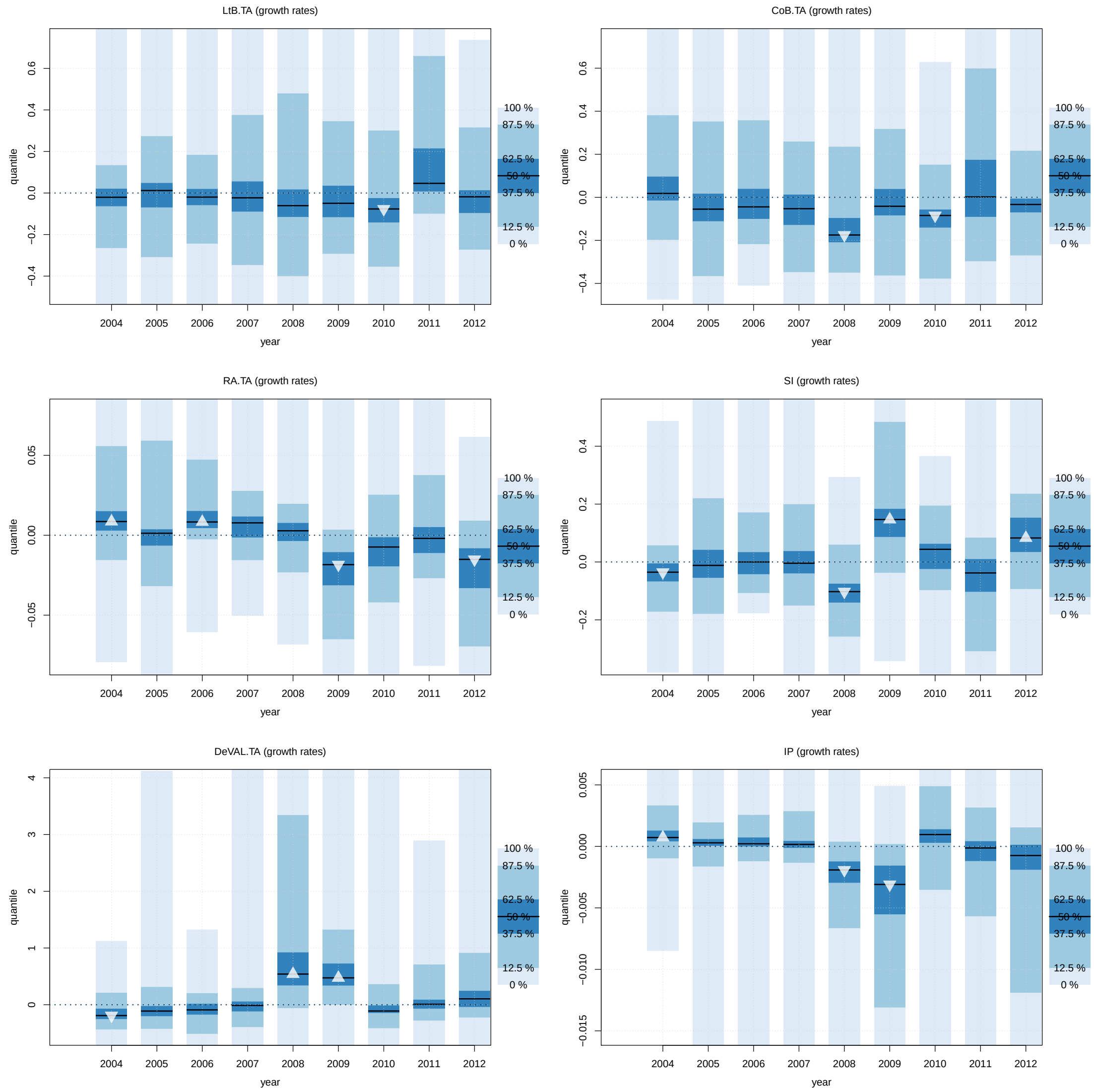

Figure 3.3: Quantile plot for the annual growth rates of LtB.TA=LtB/TA (interbank debt ratio), CoB.TA=CoB/TA, RA.TA=RA/TA, SI=Eq/RA (stability index), DeVAL.TA=DeVAL/TA and IP (information production). See figure 3.1 for more details.

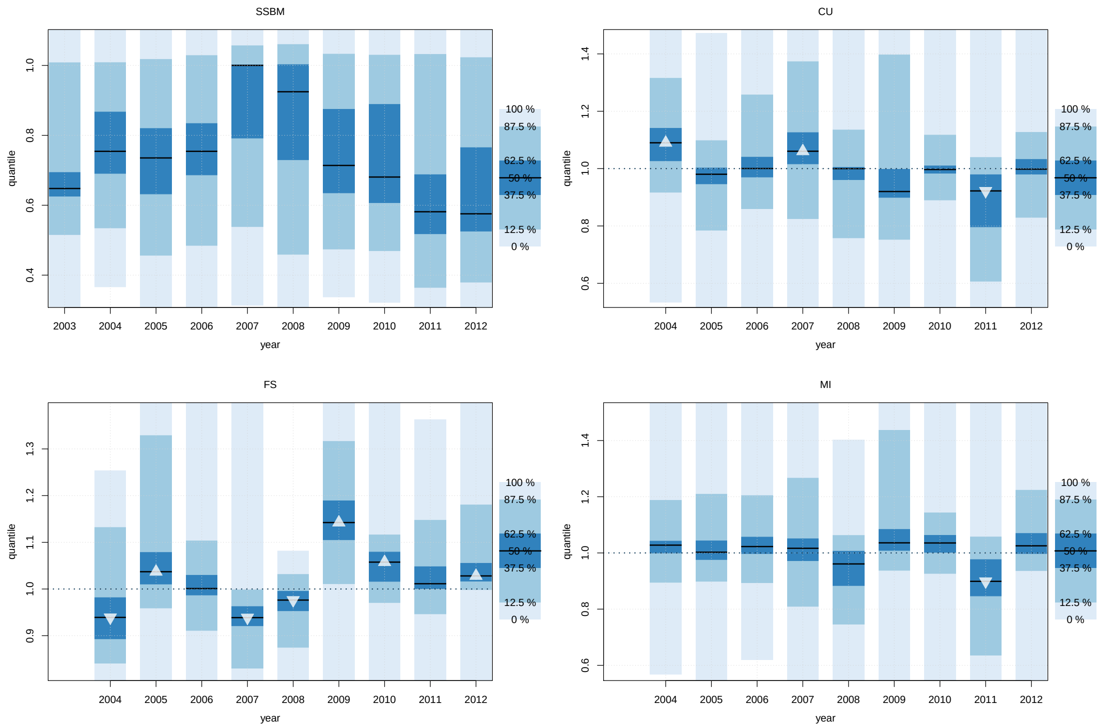

Figure 3.4: Quantile plot for the DEA efficiencies (SSBM), catch up (CU), frontier shift (FS) and the Malmquist index (MI). Here the binomial test is used to test whether the median values of CU, FS and MI respectively are equal to one. See also figure 3.1 for more details.

of four selected years are shown. Note that the percentage of efficient banks (i.e. banks with an SSBM greater than or equal to 1) is around 30% for all years except for 2007 with 52% efficient banks and 2008 where approximately 48% of the banks are efficient. This effect may be partly explained by the corresponding downward shift of the frontier (the frontier shift is significantly less than 1 in 2007 and 2008) indicating a reduction in the production possibilities of the industry in servicing the real side of the economy. The loss in efficiency, though, suffered by banks in these years is smaller than the movement of the frontier with the result of net gains in efficiency for the industry.

The evolution of the catch up (CU), of the frontier shift (FS) and of the Malmquist index (MI) is also displayed in figure 3.4. The median value of the Malmquist index is larger than one except for the years 2008 and 2011. However, the median values are close to one such that only in 2011 the binomial test signals a significant deviation from one. The low MI value in 2008 is a result of a drop of the stability index (SI) and the information production (IP) in this year. However, the small value in 2011 is harder to explain. Overall the changes from 2003 to 2012 are rather small, i.e. one cannot observe a significant improvement.

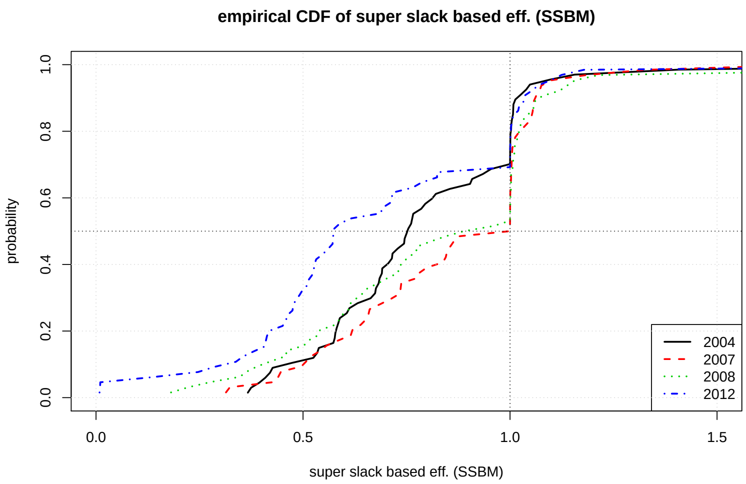

Figure 3.5: Empirical distribution function of the DEA efficiencies (SSBM) in the years 2003, 2007, 2008 and 2012.

4. Regression Analysis

In this section we discuss regression models which try to explain the development of the Malmquist index by bank specific[3] and macro economic indicators. In particular we want to relate the changes in systemic effciencies (ie. the MI index) to macro economic variables like GDP, unemployment, inflation, public debt and to indicators for the banking/financial sector like Market capitalization, Herfindahl index and so on. For a list of considered variables see table A.2.

The basic model[4] is given in table 4.1. The model explains the Malmquist index by the efficiency of the bank in the previous period (SSBM.1), the first differences of the cost-income ratio of the bank (CIR.diff), the lending spreads for household credits and credits for non financial companies and the squared differences of the government interest rates. This is a fixed effects model with both individual and time effects. Since we suspect both correlation in time as well as across the banks here and in the following we use a nonparametric robust covariance matrix estimators a la Driscoll and Kraay [1998] for panel models with cross-sectional and serial correlation. For more details see section 4.3 below.

In total we have considered about 25 candidate regressors and it is clear that there are many possible model specifications. In order to find a highly robust set of regressors we used an extreme bound analysis as described in Leamer [1985]. The estimate and the significance of a coefficient in a regression model depends on the set of regressors, i.e. adding or removing regressors in general may change the conclusions drawn on the impact of a regressor under consideration. The extreme bound analysis therefore considers a set of test models which are obtained by adding regressors out of a set of candidate variables to a base model. If the one sided t-test for a variable under consideration is significant for all test models then this variable is called robust. Otherwise it is called fragile. The five regressors chosen in the base model are *robust* in this sense. Note that we have considered test models with up to three additional regressors out of a set of 20 covariates, i.e. in total 1350 test models.

The five selected variables seem to be the most important determinants for the Malmquist index. According to the signs of the estimated coefficients we may conclude that

- non efficient banks tend to improve their relative efficiency whereas efficient banks show a tendency to loose.
- an improvement of the "operational efficiency" in terms of a decrease of the cost-income ratio implies an increase of the Malmquist index.
- (large) changes in the government interest rate tend to decrease the systemic efficiency of the banks. However, the sign of the changes of the interest rate seems to

[3] We do not consider bank variables which enter the computation of the DEA. Of course the DEA efficiencies and thus also the Malmquist index - by construction - will depend on variables like the liquidity production and thus considering these variables in a regression would only lead to trivial conclusions.

[4] All computations were carried out with R (see R Core Team [2014]) and in particular with the panel regression package plm (see Croissant and Millo [2008]).

be irrelevant.

- The lending spreads have a significant influence of the Malmquist index. However, the signs of the coefficients are inconclusive, with the Malmquist index increasing with the spread for the household credits and decreasing with the spread for loans to (non financial) companies.

On the other hand macro variables related to the economic development like GDP (growth rates) and unemployment (growth rates) are only fragile. This also holds for debt and deficit rates of the respective countries and indicators for the financial and banking sector of the countries considered. In other words our empirical analysis did not find a statistically verified influence of these variables on the development of the banking sector.

Of course this result should not be interpreted in the sense that there is no connection between the banking sector and the real economy. If we consider e.g. a regression of the GDP growth rates onto lagged GDP growth rates, the inflation rate, differences of the total debt and the Malmquist index, see table 4.2, then we get a (robust) positive influence of the MI on GDP growth.

twoways	Estimate	Std. Error	t value	Pr(>|t|)	min[	max]	#
SSBM.1	-0.806	0.105	-7.707	0.0000	-1.02	-0.72	0
CIR.diff	-0.021	0.004	-5.165	0.0000	-0.03	-0.01	0
LendingSpreadHH	0.092	0.014	6.430	0.0000	0.03	0.11	0
LendingSpreadNFC	-0.138	0.039	-3.561	0.0004	-0.31	-0.10	0
GovInterest.diff^2	-0.012	0.001	-8.379	0.0000	-0.03	-0.01	0

Table 4.1: Basic regression model for the Malmquist index. The fixed effects model contains both individual and time effects. The reported standard errors and the corresponding t-values and p-values are computed by the robust covariance estimate proposed by Driscoll and Kraay [1998]. The R-squared of the model is 0.275 and the adjusted R-Squared is 0.236. The panel is non-balanced (9 periods, 65 banks and 535 valid observations). Note that 5 out of 70 considered banks have to be skipped completely due to missing values.
The last three columns refer to the extreme bound analysis. The columns "min[" and "max]" contain the minimum (maximum) of the lower (upper) bounds of a 95% percentage confidence interval respectively. The last column (labeled "#") gives the number of test models where a one sided test (with $\alpha = 5\%$) accepts the Null.
The candidate variables are: *CIR, log(CIR), UU.diff, GDP.gr, GovInterest, GovInterest.diff, Marketcapitalization, HICP, HICP.diff, Primary_Deficit, Total_Debt.diff, Foreign_Debt.diff, Top5banks, Top5banks.diff, Credit_by_banks, Credit_by_banks.diff, stocks_trade, stocks_trade.diff, Banking_Crisis* and *log(LP.TA)*.

twoways	Estimate	Std. Error	t value	Pr(>|t|)	min[	max]	#
GDP.gr1	0.618	0.135	4.564	0.0000	-0.010	0.973	1
MI	0.024	0.008	2.948	0.0038	0.005	0.078	0
HICP	-0.005	0.002	-2.762	0.0066	-0.019	-0.005	0
Total_Debt.diff	-0.001	0.000	-4.007	0.0001	-0.003	0.0002	3

Table 4.2: Regression of GDP growth rates on the above listed variables. The Malmquist index here refers to a weighted average of the Malmquist indices of all banks of a country, where the weights are the total assets of the banks. The model is a fixed effects model with individual and time effects. The R-squared of the model is 0.42 and the adjusted R-Squared is 0.34. The panel is balanced (9 periods, 18 countries and 162 valid observations).
The candidate regressors for the extreme bound analysis are: *SSBM, SSBM1, MI1, UU.diff, HICP.diff, Primary_Deficit, Primary_Deficit.diff, Total_Debt, Foreign_Debt* and *Foreign_Debt.diff.*

4.1. Comparison with a model without time effects

Alternatively we considered a model without time effects but where some "global" regressors, i.e. regressors which only depend on the time, are added. By an analogous strategy as above we obtain the model detailed in table 4.3. Note that essentially the same set of regressors is selected, except that here four "global" regressors[5] are added.

For the extreme bounds analysis we considered models with up to three additional regressors out of a set of 23 covariates, which results in 2047 test models. The considered variables are robust with the exception of 'ECBrate.diff' (which failed in 167 models) and the 'ECBrate' (which only failed in 2 models). However, the sign of the estimated coefficients is the same for all considered test models.

The estimates for the common variables are almost the same as in the above "twoways" model. For the global variables we see that

- a rise in the stock prices for financial institutions is related to an increased efficiency of the banks.
- the ECB refinancing rate and its changes are positively correlated with the banking performance.
- The money variable M3 is negatively correlated to the Malmquist index.

A Wald test which compares the above model with the "twoways model" clearly rejects the Null (Wald test statistics W = 261.8, df = 4, p-value < 2.2e-16) and thus we proceed with the twoways model in table 4.1.

[5] Of course in a model with time effects such global regressors do not make sense.

individual	Estimate	Std. Error	t value	Pr(>|t|)	min[	max]	#
SSBM.1	-0.802	0.108	-7.434	0.0000	-1.02	-0.58	0
CIR.diff	-0.022	0.004	-5.259	0.0000	-0.03	-0.01	0
GovInterest.diff^2	-0.012	0.001	-9.198	0.0000	-0.02	-0.004	0
LendingSpreadHH	0.093	0.016	5.700	0.0000	0.03	0.15	0
LendingSpreadNFC	-0.134	0.036	-3.680	0.0003	-0.03	-0.03	0
StoxxF.gr	0.307	0.027	11.393	0.0000	0.07	0.71	0
ECBrate	0.111	0.015	7.426	0.0000	-0.04	0.29	2
ECBrate.diff	0.054	0.008	7.089	0.0000	-0.06	0.17	167
M3.gr	-3.122	0.430	-7.254	0.0000	-8.97	-0.73	0

Table 4.3: Alternative regression model for the Malmquist index. This fixed effects model only considers individual effects (i.e. bank specific dummies). The reported standard errors and the corresponding t-values and p-values are computed by the robust covariance estimate proposed by Driscoll and Kraay [1998]. The R-Squared of the model is 0.324 and the adjusted R-Squared is 0.279. The panel is non-balanced (9 periods, 65 banks and 535 valid observations). Note that 5 out of 70 considered banks have to be skipped completely due to missing variables.

The last three columns refer to the extreme bound analysis. The variables ECBrate and ECBrate.diff are *fragile*, since the union of the 95% confidence intervals of the 2047 test models contains the zero. The last column states that the one sided t-test failes in 2 and 167 respectively test models.

The candidate variables are: *CIR, log(CIR), UU.diff, GDP.gr, GovInterest, GovInterest.diff, Marketcapitalization, HICP, HICP.diff, Primary_Deficit, Total_Debt.diff, Foreign_Debt.diff, Top5banks, Top5banks.diff, Credit_by_banks, Credit_by_banks.diff, stocks_trade, stocks_trade.diff, Banking_Crisis, M1.gr, M2.gr, GDPEuro17.gr* and *log(LP.TA)*.

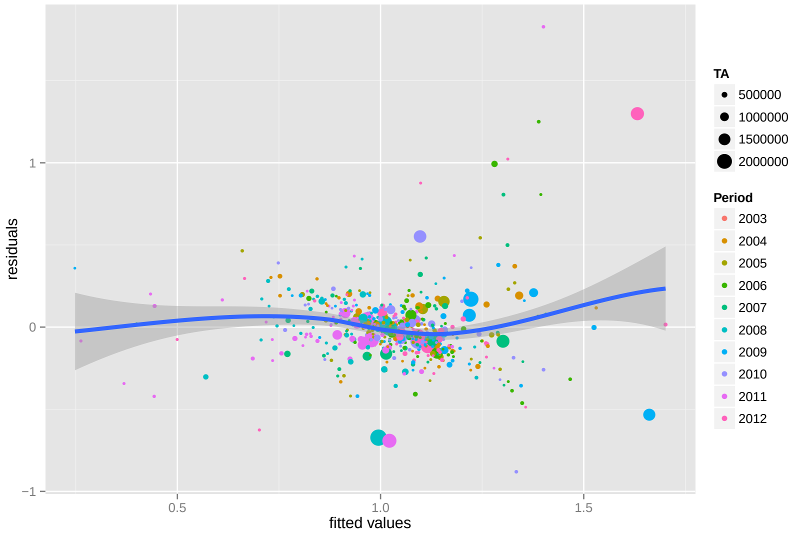

Figure 4.1: Plot of the residuals of the basic model (see table 4.1) versus the fitted values. The blue line is obtained by a local polynomial regression ('loess') of the residuals onto the fitted values. This line and the gray shaded confidence region indicate that there exist some un-modeled non linear effects.

4.2. Model Specification

The above basic model is simple in the sense that (with the exception of the differences of the Government interest rates) all variables enter linearly. Thus we perform a RESET test (of order five, i.e. we add powers of the fitted values to the regression with orders 2,...,5). All powers of the fitted values are highly significant and a Wald test clearly rejects the Null that these powers are non significant. See also figure 4.1.

Furthermore we test whether the relation between the Malmquist index and the co-variates is "stable", i.e. whether this relation changes during the evolution of crisis or whether this relation depends on specific properties of the considered banks.

First we split the time range (2004-2012) into three regimes (pre crisis 2004-2007, during the crisis 2008-2009 and post crisis 2010-2012) and check whether the coefficients are "stable", i.e. do not depend on the regime. For (GovInterest.diff^2) and CIR.diff the coefficients are not stable (as indicated by a Wald test) i.e. the dependence of the Malmquist index on these variables is different before, during and after the crisis. E.g. the depence on (GovInterest.diff^2) is stronger during the crisis.

Secondly we split the banks into 'small', 'medium', 'large', and 'huge' banks according to the total assets and question whether the bank size plays a role for the Malmquist index. It turns out that the coefficients of all variables (except for the lagged DEA efficiency SSBM.1) are unstable (according to a suitable Wald test), i.e. banks of different size react differently. In particular for huge banks the coefficient of (GovInterest.diff^2) is positive, i.e. large changes in the interest rates for Government bonds are "helpful" for huge banks but have a negative effect for small and medium banks.

Finally we also classified the considered countries as follows.

- Portugal, Ireland and Greece which received financial aid from the ESFS
- countries where a banking crisis could be observed in 2008 in the sense that significant bank nationalizations occurred and/or significant guarantees were granted
- all other countries

Here only the LendingSpreadNFC is significant (W= 9.08, p=0.011) whereas the other coefficients appear to be stable.

The above results imply that our basic model (table 4.1) is only a rough approximation of the relation between the Malmquist index and the considered covariates and may be refined in many different ways. In particular, we have investigated the impact of the lending spreads in more detail.

Looking at the outcome of our regression model we have to deal with the problem that the coefficients for the two different lending spreads have distinct signs. This effect is rather hard to explain. Therefore we were looking for transformations of these two variables where the explanation is more suitable to the real-world events. We used two simple transformations for the lending spreads:

1. LendingSpreadD = LendingSpreadHH − LendingSpreadNFC: this represents the risk premium that households have to pay more for their loans than enterprises. This difference is mostly positive, which means that normally firms are more creditworthy than households.
2. LendingSpreadS = LendingSpreadHH+LendingSpreadNFC: the sum of the two lending spreads can be interpreted as the overall credit risk in an economy.

If we replace the variables LendingSpreadHH and LendingSpreadNFC in the regression with these two transformations and if we add the product of these two transformation, we get the following results: The difference of the lending spreads is highly significant and robust with a positive sign. The product of the two transformed variables is highly significant and robust with a negative sign. The sum of the lending spreads is not significant. This means that banks in countries, where the market conditions had a bias towards lending money to corporations rather than households, performed better. In contrast to those banks, that operated in markets, where households were evaluated as creditworthy as enterprises or even better. In figure 4.2 we can see that prior to the crisis the median risk premium households had to pay for loans was sinking towards the risk premium enterprises hat to pay, reaching its minimum in 2007. This highly coincides with the triggers of the subprime crisis, were more and more cheap credits were granted to "normally" credit-un-worthy households. So banks in countries with too optimistic evaluated household creditworthiness had to make higher value adjustments due to too many bad loans. The positive effect of a clear distinction between the creditworthiness of enterprises and that of households gets weakened by the negative sign for the coefficient of

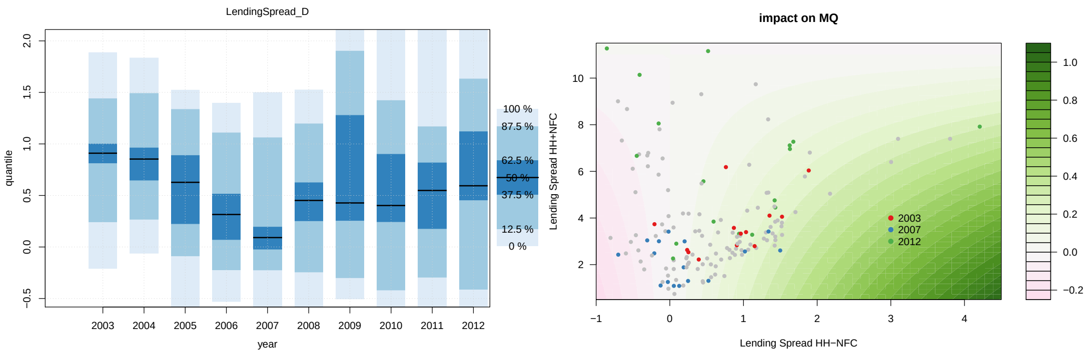

Figure 4.2: On the left hand side there is a quantile plot for the difference of the two lending spreads. The right hand side plot illustrates the impact of these lending spreads on the Malmquist index (according to the estimated coefficients). The picture shows that a large difference of the two lending spreads increases the Malmquist index. However, this effect is weakened when the overall level of the lending spreads is large.

the product term, difference between Risk premiums and overall risk premium. Meaning that in markets where the overall risk premium is high banks generally grant lesser loans and therefore don't produce as much liquidity as banks in countries with lesser credit risk. As a conclusion one can say that in years 2004-2012 the banks were getting more efficient in markets, where the market situation preferred loans to corporations over loans to households and therefore pushing banks towards lending money to corporations, which seemed to be more secure in the last decade. However, in addition the overall credit risk premium should be low to produce even more "good" liquidity.

4.3. Residual Analysis

Serial correlation of the residuals was tested both with a Breusch-Godfrey and a Wooldridge test (for panel models). The Breusch-Godfrey test rejects the Null of serially uncorrelated errors whereas the Null is accepted by the Wooldridge[6] test.

In order to check for the correlation between the banks we used a scaled LM test (Breusch and Pagan [1980]) which produced a highly significant result (test statistic z = 8.535, p-value $<$ 2.2e-16). However, this test is based on a large T asymptotics. As an alternative we also consider the CD test by Pesaran [2004] which is also useful in our context of a relatively small T. This test accepts the Null of uncorrelated errors. However, this test has a poor power in the case where there are positive and negative correlations since the test statistic is based on a (weighted) average of the estimated correlations.

A localized version of this CD test where we only consider correlations between banks

[6] The Wooldridge test is not based on a large T asymptotics and thus seems better suited for our panel where $T = 9$ and $n = 65$.

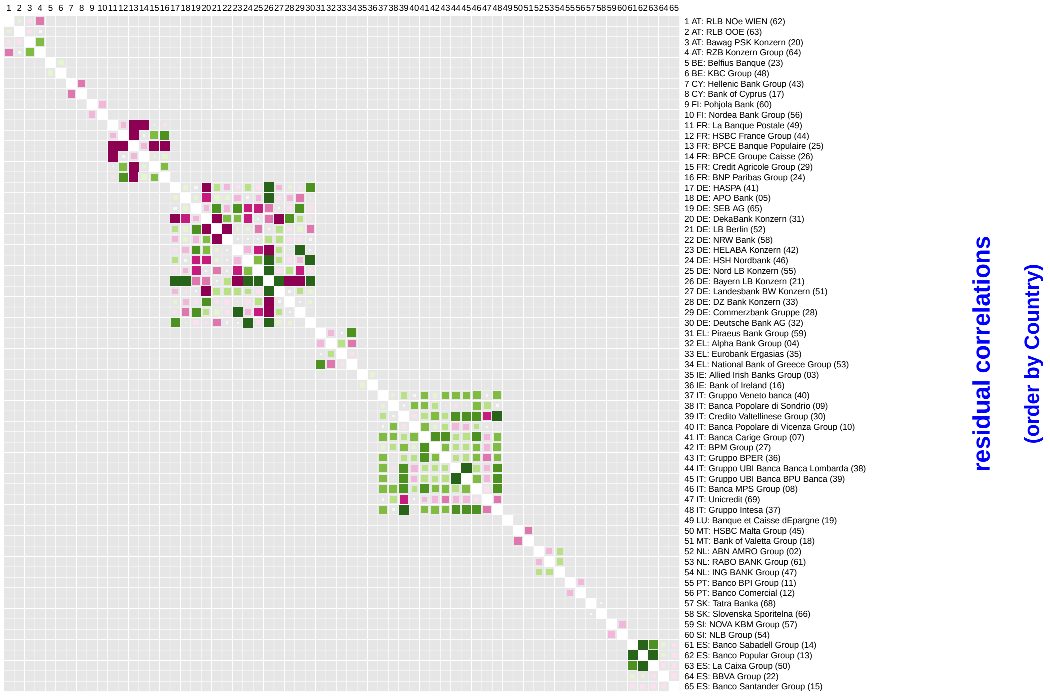

Figure 4.3: Plot of the cross sectional correlations of the residuals of the basic model (see table 4.1). Only the correlations between banks of the same country are shown, the others are grayed out. This corresponds to a localized version of the Pesaran CD test. Positive correlations are coded with green colors and negative ones with red colors. In particular note that the Italian banks are positively correlated with the exception of 'Unicredit'.

of the same country rejects the Null of no correlation between the banks (test statistic z = 3.70, p-value = 0.00022). See figure 4.3. This result (together with the highly significant scaled LM test) suggests that the residuals of this model show indeed correlation between the banks. For this reason, as has been already noted above, we use robust estimates of the covariance matrix of the estimated coefficients which take possible residual correlations into account (see Driscoll and Kraay [1998].)

5. Summary

Banks play a vital role in our economy rendering all sorts of financial intermediary services to economic agents. Current SSM-ECB regulation in our view does not consider appropriately these services but instead emphasizes on the viability of the industry and its units in order to sustain the mechanics of financial markets. This study analyses instead the systemic performance of banks in delivering intermediary financial services and puts the industry's efficiency to meet socially preferred ends in context to the behavior of selected exogenous variables.

We collected bank specific indicators (from balance sheets) of 70 banks (a subset of the ECB-defined system-relevant banks in the Euro-Zone) over 10 years (2003-2012) and have applied DEA analysis to get a grip on the systemic efficiency of the banks.

First an empirical analysis of the above mentioned indicators and of the resulting DEA efficiency scores has been used to analyze the development of the banks and their systemic efficiency during the financial crisis. It is no surprise that the crisis is clearly seen in these figures.

Second the question which economic environment is favorable for the systemic efficiency of the banks has been analyzed with a panel regression study. Here we have regressed the Malmquist index – as an indicator for the evolution of the systemic efficiencies – onto macro economic variables, variables which reflect the state of the financial system and on bank specific variables. In total we have considered about 25 candidate drivers of systemic performance of banks.

Conclusions and further research questions:

- In our study we could not find evidence of the current regulation promoting the systemic performance of banks (no visible quality effects on the bank's role as financial intermediaries)
- On the other hand, the short term instruments of the ECB could be drivers of the systemic performance as indicated by statistically significant regression coefficients for interest rate and money supply. Further studies might shed more light on these relationships.
- We have also found a dependence of the systemic performance on the cost-income ratio, lending spreads and government interest rates. However, these variables are to a great extent driven by the specific policies of the banks and thus are not strictly "exogenous". As a consequence there is little leeway for successful public policy measures.
- It would be interesting to investigate further the effects of any sort of public interventions (e.g. regulatory regimes, nationalization or governmental aid) on the system performance. Here an important prerequisite would be to define more sharply the relevant indicators to provide more details into these relationships.

A. Appendix

In this appendix we collect a list of the bank variables considered (table A.1), a list of the macro variables used (table A.2), a list of the banks (table A.3) and tables with some basic statistics (table A.4 and table A.5).

abbreviation	description	DEA
TA	total assets	input
CaB	cash and balances	
$GovS$	government (public) securities	
$DebtS$	debt securities	
LtB	liabilities to banks	
CoB	claims on banks	
CL	customer loans	
Eq	equity	
$DeVAL$	gross (sustainable) devaluation of (customer and inter-bank) loans	
CIR	cost income ratio	
$Eq.TA{=}Eq/TA$	leverage ratio (sustainability of capital)	
$RA{=}TA\text{-}CaB\text{-}GovS$	risky assets	
$RA.TA{=}RA/TA$	risk load of the bank´s (on-balance-sheet) business	input
$LtB.TA{=}LtB/TA$	interbank debt ratio	input
$LP{=}CL{+}CoB{+}DebtS$	liquidity production	output
$IP = \frac{CoB+CL}{CoB+CL-DeVAL}$	information production	output
$SI{=}\ Eq/RA$	stability index	output
$SSBM$	super slack based measure of systemic efficiency	
CU	catch up	
FS	frontier shift	
MI	Malmquist index	

Table A.1: List of the bank specific variables considered. Sources: published annual financial reporting (consolidated balance sheet and income statement) and authors calculations (SSBM, CU,FS, MI).

abbreviation	source	description
GDP	ECB	gross domestic product at market price, reference year 2005
HICP	ECB	inflation rate (Harmonised Index of Consumer Prices)
UU	ECB	unemployment rate
Primary Deficit	ECB	government primary deficit(-) or surplus(+) (as % of GDP)
Total/Foreign Debt	ECB	general government gross debt as defined in Council Regulation (EC) No 479/2009: total debt (as % of GDP) and foreign debt (as % of GDP)
GovInterest	ECB	secondary market yields of government bonds with a remaining maturity close to ten years
Herfindahl	ECB	Herfindahl index for credit institutions total assets (TA): $\sum_{i=1}^{N} a_i^2$, where $a_i = \mathrm{TA}_i \left(\sum_{j=1}^{N} \mathrm{TA}_j\right)^{-1}$
Top5banks	ECB	Shares of the 5 largest credit institutions in total assets (TA): $\left(\sum_{j=1}^{5} \mathrm{TA}_{(j)}\right)\left(\sum_{j=1}^{N} \mathrm{TA}_{(j)}\right)^{-1}$, where $\mathrm{TA}_{(j)} \geq \mathrm{TA}_{(j+1)}$
Credit by banks	WB	Domestic credit provided by banking sector (as % of GDP) (includes all credit to various sectors on a gross basis, with the exception of credit to the central government, which is net)
LendingSpread NFC/HH	ECB	weighted spread between the MIR rate for new NFC loans (loans to households) and the swap rate with a maturity corresponding to the loan category initial period of rate fixation
Market Capitalization	WB	Market capitalization (as % of GDP) is the sum of the products of share prices and respective number of shares outstanding (the sum runs over all domestically incorporated companies listed on the country's stock exchanges)
Stocks Trade	WB	stocks traded refers to the total value of shares (as % of GDP) traded during the period
Banking Crisis	IMF	is a dummy variable which indicates an ongoing banking crisis
GDPEuro17	ECB	Gross domestic product at market prices, Euro area 17 (fixed composition), reference year 2005
ECBrate	ECB	ECB (European Central Bank) refinancing rate
Euribor 1m/3m/6m/1y	ECB	Euribor rates with a maturity of 1, 3 and 6 months and 1 year
Stoxx F/B/50	ST	closing-values of the Stoxx Euro 600 Financial Service Index, Stoxx Euro 600 Banks Index and of the Euro Stoxx 50 Index
M1, M2, M3	ECB	Monetary aggregates M1, M2 and M3

Table A.2: List of the considered macro economic variables. The last five rows refer to variables which are common for all Euro countries. Sources:
- ECB: European Central Bank (`http://sdw.ecb.europa.eu`).
- WB: World Bank (`http://data.worldbank.org/`)
- ST: STOXX Limited (`http://www.stoxx.com/`)
- IMF: The banking crisis indicator is defined in Laeven and Valencia [2012].

A banking crisis starts with significant bank nationalizations and/or significant guarantees. It ends after two consecutive years of positive growth both for the GDP and the credit volumes. This paper contains the values of this indicator up to 2011. For the last year in our study (i.e. for 2012) the indicator has been computed by the authors.

iid	institute	cc	TA	TA.gr	CL	CL.gr	SSBM	MI
01	ABLV Bank	LV	1.382	31.22%	0.708	6.44%	2.218	0.927
02	ABN AMRO Group	NL	584.530	3.86%	288.786	0.74%	1.005	1.003
03	Allied Irish Banks Group	IE	140.937	2.41%	85.791	1.48%	0.775	1.037
04	Alpha Bank Group	EL	56.520	6.86%	41.284	11.97%	0.675	1.008
05	APO Bank	DE	37.479	6.85%	23.294	5.55%	0.496	0.973
06	AS SEB Banka Group	LV	3.901	6.49%	2.697	1.08%	1.013	0.979
07	Banca Carige Group	IT	29.725	12.12%	18.966	12.11%	0.817	0.904
08	Banca MPS Group	IT	187.936	5.15%	124.201	5.67%	0.581	0.999
09	Banca Popolare di Sondrio	IT	19.432	12.38%	13.669	13.50%	0.725	1.023
10	Banca Popolare di Vicenza Group	IT	28.094	13.36%	21.798	14.04%	0.699	0.958
11	Banco BPI Group	PT	41.751	6.06%	27.288	7.01%	0.685	0.987
12	Banco Comercial	PT	88.955	4.67%	64.134	3.29%	0.614	1.052
13	Banco Popular Group	ES	108.773	17.14%	89.375	12.44%	0.680	0.958
14	Banco Sabadell Group	ES	78.577	17.24%	62.502	17.00%	0.657	0.992
15	Banco Santander Group	ES	981.274	9.48%	598.994	9.12%	1.043	1.020
16	Bank of Ireland	IE	158.617	4.57%	100.280	8.55%	0.507	1.006
17	Bank of Cyprus	CY	31.398	12.83%	21.648	14.36%	0.868	0.966
18	Bank of Valetta Group	MT	5.952	5.24%	2.830	7.73%	0.789	0.975
19	Banque et Caisse dEpargne	LU	38.627	1.89%	11.230	11.82%	1.000	1.000
20	Bawag PSK Konzern	AT	43.213	-0.85%	22.755	1.78%	0.494	1.025
21	Bayern LB Konzern	DE	335.960	1.45%	153.013	-0.45%	0.821	1.097
22	BBVA Group	ES	518.396	8.13%	318.310	7.05%	0.766	1.023
23	Belfius Banque	BE	240.205	-0.61%	86.516	-2.38%	0.354	0.943
24	BNP Paribas Group	FR	1800.872	14.49%	469.752	13.22%	1.002	1.026
25	BPCE Banque Populaire	FR	376.252	8.58%	172.586	8.72%	0.762	1.061
26	BPCE Groupe Caisse	FR	625.604	8.58%	283.025	10.81%	0.744	1.090
27	BPM Group	IT	43.954	6.02%	31.309	10.52%	0.640	1.028
28	Commerzbank Gruppe	DE	620.835	1.41%	284.142	-2.03%	0.523	1.031
29	Credit Agricole Group	FR	1617.313	8.59%	536.267	6.85%	1.100	1.035
30	Credito Valtellinese Group	IT	20.396	11.47%	16.061	10.86%	0.678	0.981
31	DekaBank Konzern	DE	128.831	-2.20%	24.283	8.55%	0.515	1.453
32	Deutsche Bank AG	DE	1579.394	14.83%	337.362	4.98%	1.001	1.129
33	DZ Bank Konzern	DE	403.777	0.32%	109.552	2.76%	0.385	1.067
34	Erste Bank Group	AT	200.980	2.10%	120.071	7.31%		
35	Eurobank Ergasias	EL	68.021	13.95%	44.404	22.44%	0.808	0.914
36	Gruppo BPER	IT	50.658	4.46%	37.802	6.32%	0.685	1.013
37	Gruppo Intesa	IT	598.873	5.43%	354.653	1.75%	0.752	1.063
38	Gruppo UBI Banca Banca Lombarda	IT	121.724	3.60%	92.915	3.89%	0.746	1.036
39	Gruppo UBI Banca BPU Banca	IT	121.724	2.03%	92.915	3.69%	0.765	1.042
40	Gruppo Veneto banca	IT	19.425	22.05%	15.302	19.21%	0.957	1.007

iid	institute	cc	TA	TA.gr	CL	CL.gr	SSBM	MI
41	HASPA	DE	35.341	1.92%	22.538	5.99%	0.530	1.029
42	HELABA Konzern	DE	166.960	2.96%	82.196	2.30%	0.467	1.057
43	Hellenic Bank Group	CY	7.592	6.39%	4.143	3.84%	0.709	1.007
44	HSBC France Group	FR	204.732	5.01%	49.067	12.88%	0.435	0.919
45	HSBC Malta Group	MT	5.006	4.84%	2.967	4.97%	1.003	1.000
46	HSH Nordbank	DE	173.072	-3.90%	94.038	1.53%	0.416	1.025
47	ING BANK Group	NL	888.552	5.78%	533.935	8.61%	1.021	1.013
48	KBC Group	BE	322.527	-0.12%	135.342	6.97%	0.697	1.034
49	La Banque Postale	FR	146.627	5.43%	30.936	14.97%	1.052	0.983
50	La Caixa Group	ES	254.662	14.65%	165.032	15.81%	0.749	1.016
51	Landesbank BW Konzern	DE	389.664	1.02%	120.698	-0.21%	0.735	1.007
52	LB Berlin	DE	141.891	-1.06%	48.201	-4.37%	0.272	1.076
53	National Bank of Greece Group	EL	96.112	11.35%	61.914	12.22%	0.783	0.998
54	NLB Group	SI	15.427	3.64%	10.108	8.16%	0.581	0.977
55	Nord LB Konzern	DE	214.322	-0.76%	100.262	2.46%	0.519	1.002
56	Nordea Bank Group	FI	431.564	12.15%	254.891	10.65%	0.638	1.110
57	NOVA KBM Group	SI	5.210	7.69%	3.277	20.37%	1.102	1.029
58	NRW Bank	DE	150.048	4.99%	56.131	6.54%	1.105	0.990
59	Piraeus Bank Group	EL	47.889	18.23%	32.148	26.01%	0.605	0.949
60	Pohjola Bank	FI	26.764	11.63%	9.720	12.61%	1.001	1.000
61	RABO BANK Group	NL	588.987	7.30%	399.625	5.21%	1.021	1.009
62	RLB NOe WIEN	AT	23.541	14.17%	7.698	10.71%	0.582	1.029
63	RLB OOE	AT	29.071	9.10%	15.537	8.36%	0.510	1.026
64	RZB Konzern Group	AT	136.950	14.21%	73.963	16.21%	0.418	1.010
65	SEB AG	DE	50.395	-7.05%	21.602	-3.03%	0.809	1.000
66	Slovenska Sporitelna	SK	10.039	4.61%	5.190	21.69%	1.033	1.002
67	SWEDBANK AS	EE	16.066	1.37%	11.886	1.25%	0.691	1.037
68	Tatra Banka	SK	8.148	12.38%	4.707	17.23%	1.058	0.966
69	Unicredit	IT	322.946	11.38%	28.881	3.57%	1.004	1.033
70	Volksbanken AG Konzern	AT	47.291	-3.43%	23.892	-2.29%		

Table A.3: List of banks. The columns of this table are iid (identifier for the bank), institute (name of the bank), cc (country code), TA (median of total assets), TA.gr (total growth rate of total assets from 2003 to 2012), CL (median customer loans), CL.gr (total growth rate of customer loans from 2003 to 2012), SSBM (median DEA efficiency), MI (median Malmquist index).

variable	median	min	max	$q_{.125}$	$q_{.875}$	mean	sd	IQR	sk	#miss	#out
TA	94.987	0.362	2250.665	11.045	569.234	238.628	373.885	233.712	0.45	2	41
CL	47.243	0.093	799.005	6.053	282.201	108.886	153.076	106.297	0.43	2	42
LP	84.649	0.343	1242.841	9.834	454.028	176.453	236.212	190.677	0.39	2	29
RA	73.208	0.298	2151.354	7.779	533.582	219.732	347.424	215.384	0.56	44	41
Eq	4.134	-2.316	94.422	0.664	24.054	10.733	16.052	10.583	0.53	2	47
CaB	1.079	0.014	193.189	0.154	8.286	5.215	15.635	3.171	0.53	2	56
GovS	4.719	0.017	272.205	0.550	41.748	17.662	32.636	17.560	0.60	44	41
DebtS	13.121	0.044	377.532	1.518	95.623	39.284	60.530	46.965	0.57	2	23
LtB	14.403	0.005	495.532	1.161	102.058	39.162	60.030	48.040	0.55	2	13
CoB	7.418	0.059	259.894	0.919	69.926	28.283	43.796	34.765	0.70	2	28
DeVAL	0.335	-0.000	34.618	0.047	2.556	1.230	2.763	1.179	0.61	2	42
CL.TA	0.571	0.068	0.856	0.328	0.730	0.541	0.167	0.250	-0.24	2	0
RA.TA	0.913	0.565	0.996	0.808	0.968	0.894	0.076	0.102	-0.20	44	0
IP	0.993	0.902	1.000	0.979	0.998	0.989	0.013	0.008	-0.18	2	35
SI	0.066	-0.045	0.239	0.030	0.101	0.067	0.033	0.044	-0.09	44	1
LtB.TA	0.152	0.002	0.523	0.057	0.330	0.177	0.114	0.161	0.20	2	0
Eq.TA	0.056	-0.039	0.204	0.027	0.087	0.058	0.028	0.037	-0.03	2	1
CaB.TA	0.014	0.000	0.221	0.004	0.047	0.023	0.025	0.024	0.39	2	9
GovS.TA	0.063	0.001	0.407	0.019	0.160	0.083	0.069	0.083	0.26	44	2
DebtS.TA	0.166	0.007	0.562	0.062	0.283	0.174	0.097	0.131	0.04	2	0
CoB.TA	0.094	0.005	0.644	0.042	0.255	0.130	0.102	0.121	0.36	2	5
DeVAL.TA	0.005	-0.000	0.077	0.001	0.015	0.008	0.010	0.006	0.22	2	31
CIR	0.599	0.185	24.390	0.448	0.750	0.651	0.955	0.171	-0.04	5	8
SSBM	0.730	0.008	3.169	0.451	1.032	0.771	0.331	0.447	0.22	44	4
FS	1.010	0.411	2.055	0.893	1.170	1.033	0.163	0.128	0.14	113	12
CU	0.999	0.021	3.168	0.777	1.226	1.020	0.316	0.183	-0.05	113	30
MI	1.007	0.022	3.229	0.821	1.206	1.034	0.294	0.164	0.09	113	34

Table A.4: Basic statistics for some of the considered banking variables. The reported statics are: median, min (minimal value), max (maximum value), $q_{.125}$, $q_{.875}$ (12.5% and 87.5% quantiles), mean, sd (standard deviation), IQR (inter quartile range $q_{.75} - q_{.25}$), sk (a measure for the skewness defined as $((q_{.75} - q_{.5}) - (q_{.5} - q_{.25}))/(q_{.75} - q_{.25})$), #miss (number of missing values) and #out (number of outliers, where a value x is considered to be an outlier if $x > q_{.75} + 3(q_{.75} - q_{.25})$ or $x < q_{.25} - 3(q_{.75} - q_{.25})$ holds).

variable	period	median	max		min		%(d)	%(s)	$q_{.125}$	$q_{.875}$	IQR	sk	#out
TA	2003-2007	15.0	44.6	01	-3.1	20	36.2	2.9	6.2	26.8	12.7	0.07	0
	2008-2012	0.8	29.9	25	-22.8	67	4.3	45.7	-6.9	9.5	8.9	-0.08	0
	2003-2012	7.7	26.6	01	-3.8	02	49.3	7.2	2.0	13.8	8.6	0.13	0
CL	2003-2007	15.7	80.5	01	-11.8	52	42.0	4.3	7.0	32.0	13.1	-0.07	1
	2008-2012	0.9	63.5	69	-26.2	67	2.9	42.9	-7.1	8.4	7.6	0.06	3
	2003-2012	8.9	39.4	69	-6.0	52	56.5	7.2	1.9	17.2	7.9	-0.13	1
CL.TA	2003-2007	1.0	24.8	01	-11.0	69	1.4	36.2	-4.8	6.3	4.5	0.12	2
	2008-2012	-0.8	55.8	69	-22.1	01	1.4	57.1	-4.1	4.5	5.2	0.31	2
	2003-2012	0.7	20.0	69	-12.6	32	4.3	40.6	-1.8	3.8	3.3	0.12	2
LP.TA	2003-2007	-0.2	2.3	50	-8.4	24	0.0	66.7	-3.0	1.1	1.6	-0.06	2
	2008-2012	-0.5	7.9	02	-5.5	32	0.0	62.9	-2.0	1.6	2.3	0.22	1
	2003-2012	-0.4	0.9	27	-10.8	32	0.0	69.6	-1.7	0.4	1.4	-0.14	1
RA.TA	2003-2007	0.6	8.3	57	-1.3	22	0.0	25.4	-0.4	3.2	1.9	0.42	1
	2008-2012	-1.4	6.6	49	-8.2	01	0.0	81.2	-3.2	0.1	2.2	-0.06	1
	2003-2012	-0.3	3.0	29	-2.5	01	0.0	65.6	-1.4	1.4	1.3	0.13	0
CoB.TA	2003-2007	-2.9	39.3	59	-33.0	24	7.2	58.0	-15.9	13.7	16.9	0.21	0
	2008-2012	-5.4	39.6	06	-48.9	68	4.3	64.3	-14.7	8.0	15.6	0.18	0
	2003-2012	-5.9	15.5	43	-22.4	24	4.3	76.8	-13.3	3.2	8.0	0.14	0
LtB.TA	2003-2007	-4.1	71.7	01	-37.0	35	2.9	62.3	-13.8	9.2	12.1	0.16	2
	2008-2012	-0.5	92.9	35	-66.5	01	17.1	51.4	-18.5	25.0	24.3	0.21	1
	2003-2012	-1.8	30.6	57	-25.1	43	14.5	56.5	-11.8	8.4	10.1	0.04	0
GovS.TA	2003-2007	-10.2	63.0	50	-50.3	10	4.8	77.8	-27.9	5.1	15.4	0.12	1
	2008-2012	20.0	159.4	10	-53.3	44	51.6	25.0	-8.6	59.1	37.5	-0.05	1
	2003-2012	2.1	41.9	50	-30.6	44	31.2	45.3	-9.2	17.5	17.7	0.12	0
Eq.TA	2003-2007	0.2	29.0	58	-17.3	47	4.3	47.8	-8.8	12.0	9.0	-0.09	0
	2008-2012	3.8	40.7	46	-34.0	17	7.5	31.3	-7.1	16.9	11.8	0.16	0
	2003-2012	1.4	15.0	34	-17.3	04	7.6	39.4	-3.9	5.9	5.7	-0.34	0
SI	2003-2007	-0.3	28.5	58	-18.6	47	3.2	54.0	-10.2	11.1	10.1	-0.27	0
	2008-2012	4.7	43.2	46	-34.1	17	11.5	27.9	-5.3	18.3	12.1	0.11	0
	2003-2012	1.1	10.4	58	-17.5	17	8.2	39.3	-3.9	6.1	5.6	-0.22	0
DeVAL.TA	2003-2007	-9.0	56.2	20	-64.2	58	2.9	79.4	-24.1	7.2	14.8	-0.21	2
	2008-2012	14.5	154.5	69	-100.0	41	37.1	20.0	-5.5	46.6	21.9	-0.06	3
	2003-2012	7.1	77.5	69	-100.0	41	47.1	20.6	-2.2	18.8	12.3	0.10	2
IP	2003-2007	0.1	2.0	54	-0.8	20	0.0	23.2	-0.0	0.1	0.1	-0.13	6
	2008-2012	-0.1	0.2	01	-2.0	17	0.0	77.1	-0.6	0.0	0.4	-0.35	1
	2003-2012	-0.0	0.3	54	-0.8	17	0.0	82.6	-0.3	0.0	0.2	-0.53	1

Table A.5: Statistics for the annualized growth rates for some of the banking variables. We consider the periods 2003-2007, 2008-2012 and 2003-2012. The statistics are: median, max (maximum value and the identifier of the corresponding bank), min (minimum value and the identifier of the corresponding bank), %(d) (the percentage of banks which doubled the respective variable in the considered period), %(s) (the percentage of banks which decreased the respective variable in the period considered), $q_{.125}$, $q_{.875}$ (12.5% and 87.5% quantiles), IQR (inter quartile range $q_{.75} - q_{.25}$) and sk (a measure for the skewness defined as $((q_{.75} - q_{.5}) - (q_{.5} - q_{.25}))/(q_{.75} - q_{.25})$).

References

ECB Note Comprehensive Assessment October 2013, 2013. URL `https://www.ecb.europa.eu/pub/pdf/other/notecomprehensiveassessment201310en.pdf`.

Rajiv D. Banker, William W. Cooper, Lawrence M. Seiford, Robert M. Thrall, and Joe Zhu. Returns to scale in different dea models. *European Journal of Operational Research*, 154(2):345–362, 2004.

Edward Bernroider and Volker Stix. A method using weight restrictions in data envelopment analysis for ranking and validity issues in decision making. *Computers & Operations Research*, 34(9):2637–2647, 2007.

Trevor Stanley Breusch and Adrian Rodney Pagan. The Lagrange Multiplier Test and Its Applications to Model Specification in Econometrics. *The Review of Economic Studies*, pages 239–253, 1980.

Ana S. Camanho and R.G. Dyson. Cost efficiency, production and value-added models in the analysis of bank branch performance. *Journal of the Operational Research Society*, 56(5):483–494, 2005.

Douglas W. Caves, Laurits R. Christensen, and W. Erwin Diewert. The economic theory of index numbers and the measurement of input, output, and productivity. *Econometrica*, 50(6):pp. 1393–1414, 1982. ISSN 00129682. URL `http://www.jstor.org/stable/1913388`.

Abraham Charnes, William W. Cooper, and Edwardo Rhodes. Measuring the efficiency of decision making units. *European journal of operational research*, 2(6):429–444, 1978.

Wade D. Cook and Larry M. Seiford. Data envelopment analysis (DEA) - thirty years on. *European Journal of Operational Research*, 192(1):1 – 17, 2009. ISSN 0377-2217. doi: http://dx.doi.org/10.1016/j.ejor.2008.01.032. URL `http://www.sciencedirect.com/science/article/pii/S0377221708001586`.

William W. Cooper, Kyung Sam Park, and Gang Yu. Idea and ar-idea: Models for dealing with imprecise data in dea. *Management Science*, 45(4):597–607, 1999.

William W. Cooper, Lawrence M. Seiford, and Kaoru Tone. *Data envelopment analysis: A comprehensive text with models, applications, references and DEA-Solver Software*. Number ISBN 387452818. Springer, 2nd edition, 2007.

Yves Croissant and Giovanni Millo. Panel data econometrics in R: The plm package. *Journal of Statistical Software*, 27(2), 2008. URL `http://www.jstatsoft.org/v27/i02/`.

John C. Driscoll and Aart C. Kraay. Consistent covariance matrix estimation with spatially dependent panel data. *Review of Economics and Statistics*, 80:549–560, 1998.

Rolf Färe, Shawna Grosskopf, and C.A. Knox Lovell. *The Measurement of Efficiency of Production*, volume 6 of *Studies in Productivity Analysis*. Springer Netherlands, 1985. doi: 10.1007/978-94-015-7721-2.

Michael James Farrell. The measurement of productive efficiency. *Journal of the Royal Statistical Society. Series A (General)*, pages 253–290, 1957.

Gary Gorton and Andrew Metrick. Getting up to speed on the financial crisis: A one-weekend-readers's guide. *Journal of Economic Literature*, 50(1):128–150, 2012.

T. Joro and E.J. Viitala. Weight-restricted dea in action: from expert opinions to mathematical models. *Journal of the Operational Research Society*, 55(8):814–821, 2004.

Luc Laeven and Fabián Valencia. Systemic banking crises database: An update. Wp/12/163, International Monetary Found, June 2012.

Edward E. Leamer. Sensitivity analysis would help. *American Economic Review*, 57(3): 308–313, 1985.

John S. Liu, Louis Y.Y. Lu, Wen-Min Lu, and Bruce J.Y. Lin. Data envelopment analysis 1978–2010: A citation-based literature survey. *Omega*, 41(1):3–15, 2013.

Sten Malmquist. Index numbers and indifference surfaces. *Trabajos de Estadistica y de Investigacion Operativa*, 4(2):209–242, 1953.

Joseph C. Paradi and Haiyan Zhu. A survey on bank branch efficiency and performance research with data envelopment analysis. *Omega*, 41(1):61–79, 2013.

M. Hashem Pesaran. General diagnostic tests for cross section dependence in panels. CESifo working paper series, 2004.

Thierry Post. Performance evaluation in stochastic environments using mean-variance data envelopment analysis. *Operations Research*, 49(2):281–292, 2001.

R Core Team. *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria, 2014. URL `http://www.R-project.org/`.

Subhash C. Ray. *Data envelopment analysis: theory and techniques for economics and operations research*. Cambridge University Press, Cambridge, 2004.

R. W. Shephard. *Cost and Production Functions*. Princeton University Press, Princeton, 1953.

Kaoru Tone. A slacks-based measure of super-efficiency in data envelopment analysis. *European Journal of Operational Research*, 143(1):32 – 41, 2002. ISSN 0377-2217. doi: http://dx.doi.org/10.1016/S0377-2217(01)00324-1. URL `http://www.sciencedirect.com/science/article/pii/S0377221701003241`.