Management Quality Measurement: Using Data Envelopment Analysis (DEA) Estimation Approach for Banks in Brazil

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ABSTRACT

While the quality of a bank's management is generally acknowledged to be a key contributor to a financial institutional failure, it is usually not calculated for lack of an objective measure. This paper presents a new paradigm approach for quantifying a bank's managerial efficiency, using a data envelopment analysis (DEA) model that combines multiple inputs and outputs to compute a scalar measure of efficiency and management quality. The analysis of the largest 50 Brazilian banks over a twelve-year period from 1995 to 2006 shows significant differences in management quality scores between institutions. Hence, this new metric provides an important, but previously missing, modelling element for the early identification of troubled banks and can be used as a tool for off-site bank supervision in Brazil.

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INTRODUCTION

Over the past two decades, extensive research done by financial economists in government and academia from all over the world has gone into evaluating the efficiency of financial institutions.

The vast majority of these studies were published in the 1990s, highlighting the importance and greater frequency of this research in recent years. For example, Berger and Humphrey (1997) survey 130 studies that apply frontier efficiency analysis to financial institutions in 21 countries.

This paper uses the approach developed by Barr et al. (1992, 1993, 1994, 1997, 1998) for quantifying a bank's managerial efficiency, using an input-oriented data envelopment analysis (DEA) model that combines multiple inputs and outputs to compute a scalar measure of efficiency. This measure captures a fundamental and crucial element of a bank's success, which is its management efficiency.

In the US, bank examiners evaluate a bank's health using an overall rating system called CAMEL, based on Capital adequacy, Asset quality, Management quality, Earnings ability and Liquidity position. Financial data are the main source for scoring Capital , Asset , Earnings and Liquidity, but assessing Management is a more difficult and subjective matter.

To assess a bank's management quality, it requires professional judgment of a bank's compliance to policies and procedures, aptitude for risk-taking, development of strategic plans and the degree of bank managers in the decision making process. As Seballos and Thompson (1990) ¨the ultimate determinant of whether or not a bank fails is the ability of its management to operate the institution efficiently and to evaluate and manage risk.¨

Still, few research papers have attempted to quantify objectively management quality performance measures. And that is the purpose of this paper, to quantify banks´ management quality in Brazil using an input-oriented data envelopment analysis (DEA) model.

Data Envelopment Analysis (DEA)

DEA is a non-parametric frontier estimation methodology initiated by Charnes, Cooper and Rhodes (1978), which constructs an empirical production function that is used to compute a bank's transformational efficiency relative to its peers.

More precisely, DEA is a non-parametric estimation method which involves the application of mathematical programming to observed data to locate a frontier that can then be used to evaluate the efficiency of each of the organizational units responsible for the observed output and input quantities.

There are at least four frontier analysis methodologies used to compute financial institution efficiency, and there is no consensus among researchers on which method is best.

The approaches differ mainly in how they handle random error and their assumptions regarding the shape of the efficient frontier. The three main parametric methodologies include the stochastic frontier approach (SFA), the thick frontier approach (TFA), and the distribution-free approach (DFA).

In general, parametric approaches specify a functional form for the cost, profit, or production relationship among inputs, outputs, and environmental factors, and allow for random error.

A more useful benchmarking paradigm should have the following attributes:

- a solid economic and mathematical underpinning,
- alternative actual and composite/hypothetical best-practice units,
- the ability to take into account the trade-offs and substitutions among the benchmark metrics, and
- a means to suggest directions for improvement on the many organizational dimensions included in the study.

Data envelopment analysis, or DEA, is a non-parametric frontier estimation methodology with the above attributes. DEA computes the relative technical (or productive) efficiency of individual decision-making units by using multiple inputs and multiple outputs.

DEA has proven to be a valuable tool for strategic, policy, and operational problems, particularly in the service and nonprofit sectors. Its usefulness to benchmarking is adapted here to provide an analytical, quantitative benchmarking tool for measuring relative productive efficiency.

In general, DEA focuses on technological, or productive, efficiency rather than economic efficiency. For the purpose of this paper, productive efficiency focuses on levels of inputs relative to levels of outputs. To be productively efficient, a firm must either maximize its outputs given inputs or minimize its inputs given outputs.

Allocative efficiency is about doing the right things, productive efficiency is about doing things right, and economic efficiency is about doing the right things right. DEA was developed specifically to measure relative productive efficiency, which is the focus here.

DEA generalizes the Farrell (1957) single-output/single-input technical efficiency measure to the multiple-output/multiple-input case. DEA optimizes on each individual observation with the objective of calculating a discrete piecewise linear frontier determined by the set of Pareto-efficient decision making units (DMUs) in the case of this paper each individual bank.

Using this frontier, DEA computes a maximal performance measure for each DMU relative to all other DMUs. The only restriction is that each DMU lie on the efficient (external) frontier or be enveloped within the frontier. The DMUs that lie on the frontier are the best practice organizations and retain a value of one; those enveloped by the external surface are scaled against a convex combination of the DMUs on the frontier facet closest to it and have values somewhere between 0 and 1.

Several different mathematical programming DEA models have been proposed in the literature (see Charnes et al., 1994). Essentially, these various models each seek to establish which of *n* DMUs determine the *envelopment surfac*e, or best practice efficiency frontier. The geometry of this envelopment surface is prescribed by the specific DEA model employed.

As such, DEA is a methodology directed to frontiers rather than central tendencies.

Instead of trying to fit a regression line through the *center* of the data, DEA "floats" a piecewise linear surface on *top* of the observations. The focus of DEA is on the individual observations in contrast to the focus on the averages and estimation of parameters associated with regression approaches. Because of this unique orientation, DEA is particularly adept at uncovering relationships that remain hidden from other methodologies. DEA produces relative efficiency measures.

DEA selects the weights that maximize each firm's productive efficiency score as long as no weight is negative and the weights are universal; that is, any firm should be able to use the same set of weights to evaluate its own efficiency ratio, and the resulting ratio must not exceed one. So, for each firm, DEA maximizes the ratio of its own total weighted output to its own total weighted input. In general, the model will put higher weights on those inputs the firm uses least and those outputs the firm produces most.

Bank Examiner Rating System - CAMEL

The model used in this paper uses data envelopment analysis (DEA) to establish a proxy for the ´M´ - Management in the CAMEL rating system for banks in Brazil. This new paradigm for assessing a bank's management quality was developed by Barr et al. (1992, 1993, 1994, 1998), and it views a bank as processing multiple inputs to produce multiple outputs and focuses on its key financial intermediation functions of acquiring deposits and making loans and investments.

In the early 1970s regulators of federal financial institutions in the US, realizing the advantages of a standardized framework for the examination process, developed a rating system whereby the most critical components of a financial institution's overall safety and soundness could be identified, measured, and quantified.

In 1979, the Uniform Financial Institutions Rating System was adopted. Commonly referred to by the acronym of its component parts, the CAMEL rating, the outcome of an on-site examination of a financial institution, has become a concise and indispensable tool for examiners and regulators.

The evaluation factors that comprise an institution's CAMEL[1] rating are:

Capital adequacy
Asset quality
Management quality
Earnings ability
Liquidity

The *Commercial Bank Examination Manual* produced by the Board of Governors of the Federal Reserve System describes the five composite rating levels as follows:

CAMEL = 1 An institution that is basically sound in every respect.
CAMEL = 2 An institution that is fundamentally sound but has moderate weaknesses.
CAMEL = 3 An institution with financial, operational, or compliance weaknesses that give cause for supervisory concern.
CAMEL = 4 An institution with serious financial weaknesses that could impair future viability.
CAMEL = 5 An institution with critical financial weaknesses that render the probability of failure extremely high in the near term.

Research involving efficiency and CAMEL ratings is somewhat limited, due in large part to the restricted nature of the CAMEL ratings themselves, which are not public information. The CAMEL rating of an institution is held in strict confidence by bank regulators. The composite rating is divulged by bank regulators only to the management of the examined financial institution itself; the CAMEL component ratings are kept internal to the bank regulatory agencies.

So the approach developed in this paper is to use an input-oriented DEA model that would be used as a proxy for the M – the Management factor in the CAMEL rating for banks in Brazil. In this sense, a bank's DEA efficiency score from this model could be taken as a good proxy for managerial quality and could be used by the Central Bank of Brazil as an off-site surveillance tool to reduce the need for on-site examinations.

[1] *Note: In 1997, a sixth component was added – Sensitivity to market risk.* Each of the factors is scored from 'one' to 'five', with 'one' being the strongest rating. Additionally, a single composite CAMELS rating is determined from these components, and represents the findings of the examination for the institution as a whole.

BANK MANAGEMENT QUALITY MEASURE - DEA MODEL

In their approach Barr et al. capture the efficiency of a bank's management, the ´M´ - Management in the CAMEL system, with a transformational efficiency model described by multiple inputs and multiple outputs. The model uses data envelopment analysis (DEA) to measure a bank's performance relative to others.

This is a new approach for quantifying a bank's managerial efficiency, using a DEA model that combines multiple inputs and outputs to compute a scalar measure of efficiency; this new metric captures an elusive yet crucial element of institutional success – a bank's management quality.

US bank examiners evaluate a bank's situation with an overall rating based on Capital, Asset, Management, Earnings and Liquidity, the so-called CAMEL rating system, developed in the 1970´s. Four of the five CAMEL factors can be calculated from balance sheet and income statement data. The variable that is usually missing from financial data is the one which assesses management quality - M. This paper uses the model developed by Barr et al. around a new paradigm for assessing a bank's management quality.

This new paradigm views a bank as processing multiple inputs to produce multiple outputs and focuses on its key financial intermediation functions of acquiring deposits and making loans and investments. Using data envelopment analysis (DEA), scores for banks in Brazil are calculated yearly for the period 1995-2006. The result is an advance for the off-site supervision of banks´ management quality.

Overall, bank managers must integrate policies and techniques for transforming inputs (resources) into outputs, for managing the money position providing liquidity, lending profitably, and investing rationally into a practical asset/liability management framework. The most efficient banks do this by controlling operating expenses, managing interest rate sensitivity, utilizing risk management techniques and strategically planning for the bank and its future markets.

In their research, Barr et al. confirm that the quality of management is crucial to a bank's survival.

In this paper, we use an input-oriented data envelopment analysis (DEA) model to benchmark the productive efficiency of banks in Brazil. Using the DEA model developed by Barr et al. (1992, 1993, 1994, 1997, 1998, 1999), we measure relative productive efficiency of these financial institutions over a 12-year period from 1995 to 2006.

In the Barr et al. model, a bank is a transformer of multiple inputs into multiple outputs and a bank's DEA efficiency score from this captures the essential financial intermediation functions of a bank.

The DEA model approximates the decision-making nature of bank management by incorporating the necessary input allocation and product mix decisions needed to attract deposits and make loans and investments. In this paper, the input-oriented DEA model has four inputs and three outputs. The inputs represent resources required to operate a bank: number of employees, labor costs, number of branches, and funding costs. The outputs represent desired outcomes: deposits, savings and interest income.

According to this model, productively efficient banks, or best-practice banks, allocate resources and control internal processes by effectively managing their employees, facilities, expenses, and sources and uses of funds while working to maximize earning assets and income.

DATA

The source for the data used in this paper is the Central Bank of Brazil website (www.bacen.gov.br). In its website, the Central Bank of Brazil publishes quarterly data, balance sheets and income statements, from 1995 concerning the 50 largest banks in the Brazilian financial system, which represent more than 90% of the banking system in terms of total assets. All the data for the multiple inputs and outputs used in this paper's DEA model were taken directly from this website, using end of the year data from 1995 to 2006 for all the 50 largest banks for each of the 12 years analyzed.

SOFTWARE

The software used in this paper to calculate the DEA frontier is called OnFront. Economic Measurement and Quality (EMQ) was established in 1993 by a team of professional economists and it has developed OnFront, a software for measuring economical productivity and quality. The efficiency and productivity measures in OnFront include Malmquist productivity indexes and DEA. OnFront was developed by the originators of the Malmquist productivity index.

This software constructs a benchmark for each individual organization that is based on actual observed achievements in similar organizations. This benchmark is called the best practice frontier. This is sometimes also referred to as the reference technology, production frontier or just technology. The frontier is constructed from observations of what is called inputs and outputs.

For a reference technology, the model in this paper exhibits Variable Returns to Scale - VRS, the intensity variables are restricted to sum exactly one, rather than Constant Returns to Scale - CRS, where proportional changes in outputs require proportional changes in inputs. Also in this paper, the model uses Strong Disposability of Inputs, i.e., if inputs are held the same, or increased, then output will not decrease. Strong disposability of inputs means that an increase in inputs cannot decrease outputs.

RESULTS

The results of the input-oriented DEA model efficiency scores of the 50 largest banks in Brazil from 1995 to 2006 are presented in the Appendix. Banks are ranked by size from larger to smaller. DEA efficiency scores cannot be compared from year to year because they reveal relative efficiencies for the time period under analysis, meaning that they are only comparable with peer scores for each specific year. Also, the group of 50 largest banks is different from the previous year, due to mergers, acquisitions, bank failures, and changes in the banks´ rankings.

For each of the years in the period analyzed, around half of the 50 banks have efficiency scores of 1.00, which represent the best-practice organizations, the institutions that are on the efficiency frontier, and the other half of the banks show an efficiency score below the best-practice institutions, or below 1.00 in every year.

Additionally, the five largest Brazilian banks, among them two public banks, namely Banco do Brasil (BB) and Caixa Econômica Federal (CEF), and the three largest privately-owned banks, namely Bradesco, Itaú and Unibanco, all reveal an efficiency score of 1.00 in each year during this period. That finding is surprising since there is strong criticism in Brazil against publicly-owned banks that are supposedly inefficient. But in the DEA model used here, the largest public banks show scores that are as efficient as the ones in the largest private banks.

The average input-oriented DEA efficiency score for the 50 largest banks has changed significantly between 1995 and 2006, with a minimum score of 0.74 in 2002 and a maximum score of 0.87 in 2005. For 2006, the average score was 0.82. The minimum efficiency score for each year also has varied along these years, going from 0.41 in 1996 to 0.18 in 2005. This means that the least efficient banks have become even less efficient in the period under analysis.

An illustrative example is a bank named Santos, its efficiency score evolved as follow: 1.00 in 2000, 0.43 in 2001, 0.26 in 2002, 0.62 in 2003 and 0.66 in 2004. Not surprisingly, the clear deterioration of its DEA score initially demonstrated its weakening efficiency, which translated into a Central Bank intervention in 2004.

Another surprising descriptive example refers to the Spanish bank Santander, which acquired bank Banespa, the largest state-owned bank in Brazil, in 2000. Previous to Santander´s acquisition, Banespa had efficiency scores of 1.00 in every year from 1995 to 2000, while Santander had an efficiency score of 0.47 in 1999. After the acquisition, Santander efficiency score evolved as follows: it increased from 0.72 in 2000 to 0.8 in 2001, and then decreased to 0.68 in 2002; but it increased again to 0.74 in 2003, to only decrease once more to 0.71 in 2004, and 0.69 in 2005; and finally increased once again to 0.79 in 2006. This shows a completely different view from the mainstream analysis that Banespa was an inefficient bank, while Santander, as a foreign bank, was efficient. Using the DEA model developed in this paper, the results are the opposite, Santander was an inefficient bank when it acquired Banespa, and on average Santander improved its efficiency score during the post-acquisition period.

Still an unexpected result is the one that refers to another Spanish bank, BBVA. It consistently had very low and decreasing efficient scores according to the DEA model developed in this paper, 0.39 in 1998, the year BBVA started its operation in Brazil, to 0.40 in 1999, 0.38 in 2000, 0.33 in 2001 and 0.33 in 2002. Not surprisingly, BBVA sold in 2003 its business in Brazil to Bradesco, the largest privately owned bank in the country.

These unpredicted findings corroborate the usefulness of the DEA model efficiency scores calculated using data from the Central Bank of Brazil, to assess a bank's management quality.

CONCLUSION

The financial institution efficiency literature is both large and relatively recent. Berger and Humphrey (1997) report that 116 out of the 130 studies that apply frontier analysis to determine financial institution efficiency were published from 1992 to 1997. Berger and Humphrey also report that there are now enough frontier analysis studies to draw some tentative comparisons of average efficiency levels both across measurement techniques and across countries, as well as outline the primary results of the many applications of efficiency analysis to policy and research issues. They find that overall, depository financial institutions banks, savings and loans, and credit unions experience annual average technical efficiency ratios of around 77%[2] (median 82%).

DEA is a non-parametric frontier analysis estimation methodology initiated by Charnes et al. (1978), which constructs an empirical production function that is used to compute a bank's transformational efficiency relative to its peers. More precisely, DEA is a non-parametric estimation method which involves the application of mathematical programming to observed data to locate a frontier which can then be used to evaluate the

[2] A 77 % efficiency measure typically means that if the average firm were producing on the frontier instead of at its current location, then only 77 % of the resources currently being used would be necessary to produce the same output (or meet the same objectives).

efficiency of each of the organizational units responsible for the observed output and input quantities. As such, DEA is a methodology directed to frontiers rather than central tendencies. DEA is an alternative and a complement to traditional central-tendency (statistical regression) analyses, and it provides a new approach to traditional cost–benefit analyses and frontier (or best-practices) estimation. DEA is a linear-programming based technique that converts multiple inputs and multiple outputs into a scalar measure of relative productive efficiency. Thus, the initial problem is the construction of an empirical production frontier based on the observed data. DEA constructs such an empirical production frontier. More precisely, DEA is a non-parametric frontier estimation method that involves applying linear programming to observed data to locate the best-practice frontier. This frontier can then be used to evaluate the productive efficiency of each of the organizational units responsible for the observed output and input quantities.

Bank supervision includes on-site examination and off-site surveillance. The role of off-site bank supervision entails mostly continuous monitoring of profitability, risk and capital adequacy. This involves using financial data to schedule and plan on-site exams. Off-site surveillance also helps supervisors plan on-exams by highlighting risk exposures at specific institutions.

The utilization of bank management quality as measured by DEA scores, such as those calculated in this paper using data from the Central Bank of Brazil, has significant potential as an instrument of indirect supervision to identify potential risks in banks before they materialize.

In this research paper, we used an input-oriented DEA model to evaluate the relative productive efficiency of banks in Brazil. The goal is to benchmark the productive efficiency of banks and this is accomplished by comparing the volume of services provided and resources used by each bank with those of all other banks in each year.

The new idea is that this productive efficiency measure can provide an indicator to benchmark performance and is conceptually superior to measures produced using common gap analysis methodologies. Previous research has shown that more efficient banks tend to be higher performers and safer institutions.

The multiple input-output DEA model used in this paper is an objective measure to quantify management quality in banks in Brazil. Management is indeed important to the successful operation of a bank and the quality of management is crucial for a bank's survival.

It is therefore imperative that bank managers and regulators understand where banks stand relative to competitors and best practices regarding their productivity. A more inclusive multiple-input, multiple-output framework for evaluating productive efficiency and providing benchmarking information on how to become a well-managed bank seems essential to improving decision making at poorly managed banks.

The calculated DEA efficiency scores can be useful as a complementary off-site monitoring tool for bank regulators. Its usefulness to benchmarking is adapted here to provide an analytical, quantitative benchmarking tool for measuring relative productive efficiency. Banks with low efficiency scores should be closely monitored.

While the quality of a bank's management is generally acknowledged to be a key contributor to a financial institutional failure, it is usually not calculated for lack of an objectively measure. This paper presents a new paradigm approach for quantifying a bank's managerial efficiency, using a DEA model that combines multiple inputs and outputs to compute a scalar measure of efficiency and management quality. An analysis of the largest 50 Brazilian banks over a twelve-year period shows significant differences in management-quality scores between institutions in this period. Hence this new metric provides an important, yet previously missing, modelling element for the early identification of troubled banks and can be used as a tool for off-site bank supervision in Brazil.

A suggestion for further research is to use the CAMEL scores from the Central Bank of Brazil and compare them to the DEA model scores developed in this paper and contrast them to check whether they are significantly different or not. But since CAMEL scores are undisclosed, it would require public access to that kind of information.

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APPENDIX

Input-oriented DEA scores for largest 50 Brazilian banks from 1995 to 2006

2006	Fi(y,x/V,S)	2005	Fi(y,x/V,S)	2004	Fi(y,x/V,S)
BB	1,00	BB	1,00	BB	1,00
BRADESCO	0,97	CEF	1,00	CEF	1,00
CEF	1,00	BRADESCO	1,00	BRADESCO	1,00
ITAU	1,00	ITAU	1,00	ITAU	1,00
ABN AMRO	1,00	UNIBANCO	1,00	UNIBANCO	1,00
SANTANDER BANESPA	0,79	SANTANDER BANESPA	0,69	SANTANDER BANESPA	0,71
UNIBANCO	0,89	ABN AMRO	0,88	ABN AMRO	1,00
SAFRA	1,00	SAFRA	1,00	SAFRA	1,00
HSBC	0,73	HSBC	0,68	HSBC	0,79
VOTORANTIM	1,00	VOTORANTIM	1,00	NOSSA CAIXA	1,00
NOSSA CAIXA	1,00	NOSSA CAIXA	1,00	VOTORANTIM	1,00
CITIBANK	1,00	CITIBANK	1,00	CITIBANK	1,00
UBS PACTUAL	1,00	BANKBOSTON	1,00	BANKBOSTON	1,00
BANRISUL	0,93	PACTUAL	1,00	BNB	0,55
BBM	0,76	BANRISUL	0,98	BANRISUL	0,97
BNB	0,62	BNB	0,64	CREDIT SUISSE	0,95
ALFA	1,00	BBM	0,31	ALFA	0,26
DEUTSCHE	0,52	ALFA	0,34	JP MORGAN CHASE	0,36
CREDIT SUISSE	0,55	DEUTSCHE	0,53	PACTUAL	1,00
JP MORGAN CHASE	0,35	JP MORGAN CHASE	1,00	SANTOS - Sob Intervenção	0,66
FIBRA	1,00	CREDIT SUISSE	0,64	BNP PARIBAS	0,25
BIC	0,34	BIC	0,28	BBM	0,56
BNP PARIBAS	0,25	BNP PARIBAS	0,26	RURAL	0,65
BASA	0,94	BASA	1,00	DEUTSCHE	0,33
BANESTES	1,00	BMG	0,52	BIC	0,35
BMG	0,63	BANESTES	0,93	BASA	0,65
BESC	1,00	MERCANTIL DO BRASIL	0,48	MERCANTIL DO BRASIL	0,49
MERCANTIL DO BRASIL	0,63	RABOBANK	1,00	RABOBANK	1,00
IBIBANK	1,00	FIBRA	1,00	BANESTES	0,91
ABC-BRASIL	0,44	ABC-BRASIL	0,44	FIBRA	1,00
RABOBANK	1,00	BESC	0,72	BMG	1,00
SS	1,00	IBIBANK	1,00	SS	1,00
BANCOOB	0,58	SS	1,00	ABC-BRASIL	0,47
PINE	0,72	RURAL	0,60	CRUZEIRO DO SUL	0,53
ING	1,00	CRUZEIRO DO SUL	0,51	BESC	1,00
BRB	1,00	BRB	1,00	IBIBANK	1,00
DAYCOVAL	0,79	BANCOOB	1,00	BRB	1,00
BMC	0,54	PINE	0,77	BANCOOB	0,63
CLASSICO	1,00	BEC	1,00	BMC	0,29
BANSICREDI	1,00	AMEX	0,18	DRESDNER	0,40
BARCLAYS	1,00	BMC	0,40	CREDIT LYONNAIS	0,59
CRUZEIRO DO SUL	0,50	CLASSICO	1,00	AMEX	0,22
SOFISA	0,92	DAYCOVAL	0,59	WESTLB	1,00
BGN	0,35	ING	1,00	BEC	1,00
WESTLB	1,00	SOFISA	0,74	CLASSICO	1,00
RURAL	0,62	BANSICREDI	0,80	BCO JOHN DEERE	1,00
BCO JOHN DEERE	1,00	WESTLB	1,00	SOFISA	1,00
SCHAHIN	1,00	BCO JOHN DEERE	1,00	PINE	0,88
BANESE	1,00	SOCIETE GENERALE	1,00	ING	1,00
BANIF	0,42	BGN	0,48	DAYCOVAL	0,59
AVERAGE	0,82	AVERAGE	0,79	AVERAGE	0,78

2003	Fi(y,x/V,S)	2002	Fi(y,x/V,S)	2001	Fi(y,x/V,S)
BB	1,00	BB	1,00	BB	1,00
CEF	1,00	CEF	1,00	CEF	1,00
BRADESCO	1,00	BRADESCO	1,00	BRADESCO	1,00
ITAU	1,00	ITAU	1,00	ITAU	1,00
UNIBANCO	1,00	UNIBANCO	1,00	SANTANDER BANESPA	0,80
ABN AMRO	1,00	SANTANDER BANESPA	0,68	UNIBANCO	1,00
SANTANDER BANESPA	0,74	ABN AMRO	0,77	ABN AMRO	1,00
SAFRA	1,00	CITIBANK	1,00	SAFRA	1,00
NOSSA CAIXA	1,00	NOSSA CAIXA	1,00	BANKBOSTON	1,00
HSBC	0,83	HSBC	0,99	CITIBANK	1,00
CITIBANK	1,00	BANKBOSTON	1,00	NOSSA CAIXA	1,00
VOTORANTIM	1,00	SAFRA	1,00	HSBC	0,71
BANKBOSTON	1,00	VOTORANTIM	0,62	SUDAMERIS	0,74
BNB	0,65	SUDAMERIS	0,65	BBA-CREDITANSTALT	0,91
BANRISUL	0,87	BILBAO VIZCAYA	0,33	VOTORANTIM	0,55
CREDIT SUISSE	1,00	BANRISUL	0,84	BILBAO VIZCAYA	0,33
SANTOS	0,62	BNB	0,81	BNB	0,31
ALFA	0,58	JP MORGAN CHASE	0,21	BANRISUL	0,78
JP MORGAN CHASE	0,25	LLOYDS	0,81	LLOYDS	0,74
RURAL	0,77	SANTOS	0,26	MERCANTIL SP	0,44
PACTUAL	0,58	ALFA	0,35	DEUTSCHE	0,81
DEUTSCHE	0,33	RURAL	0,35	JP MORGAN CHASE	0,20
BASA	0,57	BASA	0,26	CREDIT SUISSE	1,00
BIC	0,62	BNP PARIBAS	0,36	PACTUAL	1,00
BBM	0,72	CREDIT SUISSE	1,00	SANTOS	0,43
BNP PARIBAS	0,32	FIBRA	1,00	ALFA	1,00
FIBRA	1,00	WESTLB	0,33	RURAL	0,63
MERCANTIL DO BRASIL	0,63	ABC-BRASIL	1,00	BASA	0,34
RABOBANK	1,00	RABOBANK	1,00	ABC-BRASIL	1,00
BANESTES	1,00	PACTUAL	0,59	BNL	0,53
BESC	0,84	ING	1,00	MERCANTIL DO BRASIL	0,61
ABC-BRASIL	0,60	MERCANTIL DO BRASIL	0,42	BNP PARIBAS	0,38
SS	1,00	BIC	0,39	EUROPEU	0,33
BMC	0,70	TOKYOMITSUBISHI	1,00	DRESDNER	1,00
WESTLB	1,00	BANESTES	0,74	BRASCAN	0,50
CRUZEIRO DO SUL	0,74	DRESDNER	0,42	BANESTES	0,94
BMG	0,79	DEUTSCHE	0,38	FIBRA	1,00
TOKYOMITSUBISHI	0,73	BNL	0,57	ING	1,00
ING	1,00	BESC	0,70	TOKYOMITSUBISHI	1,00
BRB	1,00	BRASCAN	0,58	BIC	0,43
BANCOOB	1,00	SS	1,00	BESC	1,00
BVA	1,00	BRB	1,00	RABOBANK	1,00
LLOYDS	1,00	SOFISA	0,55	SS	1,00
BNL	0,71	BMC	0,48	BBM	1,00
DRESDNER	1,00	BMG	0,61	BRB	1,00
BEC	1,00	SMBC	1,00	BEG	1,00
PINE	1,00	BANCOOB	1,00	SMBC	1,00
SOFISA	0,89	SUL AMERICA	1,00	PROSPER	1,00
SMBC	1,00	BBM	1,00	BARCLAYS GALICIA	1,00
CACIQUE	0,88	BEC	1,00	BMC	0,68
AVERAGE	0,84	AVERAGE	0,74	AVERAGE	0,80

2000	Fi(y,x | V,S)	1999	Fi(y,x | V,S)	1998	Fi(y,x | V,S)
BB	1,00	BB	1,00	BB	1,00
CEF	1,00	CEF	1,00	CEF	1,00
BRADESCO	1,00	BRADESCO	1,00	BRADESCO	1,00
ITAU	1,00	ITAU	1,00	ITAU	1,00
UNIBANCO	1,00	UNIBANCO	1,00	UNIBANCO	1,00
BANESPA	1,00	BANESPA	1,00	BANESPA	1,00
ABN AMRO	1,00	ABN AMRO	1,00	REAL	0,92
SANTANDER BRASIL	0,72	SAFRA	1,00	BANRISUL	0,64
SAFRA	1,00	NOSSA CAIXA	1,00	HSBC	0,86
HSBC	0,85	BANKBOSTON	1,00	NOSSA CAIXA	1,00
NOSSA CAIXA	1,00	SANTANDER BRASIL	0,47	SAFRA	1,00
BANKBOSTON	1,00	CITIBANK	1,00	SANTANDER BRASIL	0,45
CITIBANK	1,00	HSBC	0,65	SUDAMERIS	0,78
BBA-CREDITANSTALT	1,00	BBA-CREDITANSTALT	1,00	ABN AMRO	1,00
SUDAMERIS	0,78	SUDAMERIS	0,72	CITIBANK	1,00
BILBAO VIZCAYA	0,38	BILBAO VIZCAYA	0,40	BBA-CREDITANSTALT	1,00
BNB	0,78	BANDEIRANTES	0,66	BANKBOSTON	1,00
MERCANTIL SP	0,86	MERCANTIL FINASA	0,59	MERCANTIL FINASA	0,58
BANRISUL	0,77	BNB	1,00	BNB	0,98
VOTORANTIM	0,56	MERIDIONAL	0,51	MERIDIONAL	0,55
LLOYDS	0,94	BANRISUL	0,76	BILBAO VIZCAYA	0,39
CHASE	0,31	BANESTADO	0,59	BANDEIRANTES	0,71
ALFA	1,00	LLOYDS	1,00	BANESTADO	0,48
CSFB GARANTIA	1,00	VOTORANTIM	0,68	BOAVISTA	0,37
SANTOS	1,00	BOAVISTA	0,40	VOTORANTIM	1,00
RURAL	0,82	CSFB GARANTIA	0,56	LLOYDS	0,91
MERCANTIL DO BRASIL	0,69	CHASE	0,39	CHASE	0,83
BASA	0,65	ALFA	1,00	BBM	1,00
DRESDNER	1,00	RURAL	0,65	RURAL	0,63
BBM	1,00	DEUTSCHE	1,00	CSFB GARANTIA	1,00
ABC-BRASIL	0,64	JP MORGAN	0,52	PONTUAL	1,00
BANESTES	0,90	BARCLAYS GALICIA	1,00	ING	1,00
EUROPEU	0,37	DRESDNER	1,00	BANEB	1,00
BNL	0,50	BBM	1,00	DRESDNER	1,00
MORGAN	1,00	BASA	0,88	DEUTSCHE	0,68
DEUTSCHE	1,00	BEG	0,52	BIC	0,64
ING	1,00	BIC	0,55	BESC	0,61
BARCLAYS GALICIA	1,00	MERCANTIL DO BRASIL	0,52	JP MORGAN	0,79
BIC	0,58	ING	1,00	BMB	0,47
PACTUAL	0,78	PACTUAL	0,55	BARCLAYS GALICIA	1,00
BESC	1,00	BANESTES	1,00	BMC	0,80
FIBRA	1,00	BEAL	0,62	CREDIBANCO	1,00
TOKYOMITSUBISHI	1,00	ABC-BRASIL	1,00	BASA	0,60
BRASCAN	0,62	CREDIBANCO	0,79	TOKYOMITSUBISHI	1,00
BRB	1,00	BNL	0,67	FIBRA	1,00
RABOBANK	1,00	TOKYOMITSUBISHI	1,00	BMG	1,00
FININVEST	1,00	BMC	0,90	BEG	0,54
SS	1,00	AGF BRASEG	1,00	PACTUAL	0,80
BEG	0,88	BRB	1,00	BEAL	1,00
BMC	0,75	FIBRA	1,00	BRB	1,00
AVERAGE	0,86	AVERAGE	0,81	AVERAGE	0,84

1997	Fi(y,x/V,S)	1996	Fi(y,x/V,S)	1995	Fi(y,x/V,S)
CEF	1,00	CEF	1,00	CEF	1,00
BB	1,00	BB	1,00	BB	1,00
BANESPA	1,00	BANESPA	1,00	BANESPA	1,00
ITAU	1,00	BRADESCO	1,00	BRADESCO	1,00
BRADESCO	1,00	ITAU	1,00	UNIBANCO	1,00
UNIBANCO	1,00	UNIBANCO	1,00	ITAU	1,00
REAL	0,88	REAL	1,00	BAMERINDUS	0,94
NOSSA CAIXA	1,00	BAMERINDUS	0,67	REAL	1,00
BEMGE	0,41	NOSSA CAIXA	1,00	NOSSA CAIXA	1,00
BANRISUL	0,53	BANRISUL	1,00	BANRISUL	0,68
SAFRA	1,00	CREDIREAL	0,43	SAFRA	1,00
HSBC BAMERINDUS	0,59	SAFRA	1,00	CREDIREAL	0,40
BAMERINDUS	1,00	CITIBANK	1,00	BANERJ	0,76
BCN	0,79	BCN	0,73	BCN	0,92
BANKBOSTON	0,81	BANESTADO	0,91	BNB	1,00
CITIBANK	1,00	SUDAMERIS	0,95	BANESTADO	1,00
BANESTADO	0,58	BANKBOSTON	0,55	SUDAMERIS	1,00
BOAVISTA	0,41	MERCANTIL SP	0,55	CITIBANK	1,00
SUDAMERIS	0,94	BOAVISTA	0,46	BANKBOSTON	0,37
BBA-CREDITANSTALT	1,00	BNB	0,72	BBA-CREDITANSTALT	0,91
MERCANTIL SP	0,65	BBA-CREDITANSTALT	0,78	MERCAPAULO	0,59
EXCEL	0,52	BOZANO,SIMONSEN	1,00	BOAVISTA	0,66
BNB	0,64	BANDEIRANTES	0,67	LLOYDS	0,57
ABN AMRO	1,00	BBV BANCO	0,42	AMERICA DO SUL	0,95
BANDEIRANTES	0,78	AMERICA DO SUL	0,85	BCO BFB	0,89
BOZANO,SIMONSEN	0,58	ABN AMRO	1,00	BOZANO,SIMONSEN	1,00
AMERICA DO SUL	0,80	LLOYDS	0,44	ABN AMRO	0,57
LLOYDS	1,00	BEMGE	0,56	BEMGE	0,79
GARANTIA	0,87	BMC	0,58	MERIDIONAL	0,82
CHASE	0,60	BIC	0,46	BCO BANDEIRANTES	0,49
JP MORGAN	0,98	MERIDIONAL	0,52	PONTUAL	0,85
VOTORANTIM	1,00	CHASE	0,63	BANEB	0,73
SANTANDER BRASIL	0,31	PONTUAL	0,87	BANCO BMC	0,90
MERIDIONAL	0,69	BANEB	0,75	BESC	0,74
BANEB	0,86	BESC	0,77	DIBENS	1,00
BIC	0,51	DIBENS	1,00	JP MORGAN	1,00
BESC	0,63	PACTUAL	1,00	BMB	0,72
FIBRA	0,65	FIBRA	0,50	EXCEL	0,95
BMC	0,69	BMB	0,45	PACTUAL	1,00
ING BANK	0,61	DEUTSCH	1,00	CREDIBANCO	1,00
CREDIBANCO	0,77	CREDIBANCO	0,82	VOTORANTIM	1,00
PONTUAL	0,87	RURAL	0,41	BRB	1,00
PACTUAL	0,87	BMG	1,00	BIC	0,84
DIBENS	1,00	BRB	1,00	CHASE MANHATTAN	1,00
RURAL	0,36	JP MORGAN	0,82	DEUTSCHE	1,00
BARCLAYS	0,79	GERAL DO COMERCIO	0,50	FIBRA	0,91
DEUTSCHE	0,64	BANESTES	0,91	RURAL	0,78
BMG	1,00	BNL	0,87	BASA	0,80
BMB	0,53	BASA	0,80	BMG	1,00
BRB	1,00	VOTORANTIM	1,00	GERAL DO COMERCIO	0,87
AVERAGE	0,78	AVERAGE	0,79	AVERAGE	0,87