PRODUCTIVITY GROWTH IN EUROPEAN BANKING

Carmen Murillo-Melchor
José Manuel Pastor
Emili Tortosa-Ausina

FUNDACIÓN DE LAS CAJAS DE AHORROS
DOCUMENTO DE TRABAJO
Nº 207/2005

De conformidad con la base quinta de la convocatoria del Programa de Estímulo a la Investigación, este trabajo ha sido sometido a evaluación externa anónima de especialistas cualificados a fin de contrastar su nivel técnico.

ISBN: 84-89116-07-5

Productivity growth in European banking*

Carmen Murillo-Melchor[†] José Manuel Pastor[‡] Emili Tortosa-Ausina[§]

May, 2005

Abstract

This article analyzes productivity growth for European banks over the 1995–2001 period. In contrast to previous literature, the study encompasses the overwhelming majority of current European Union (EU) countries—all excepting Greece and those joining the EU in 2004. In addition, we use resampling methods so as to gain statistical precision, which turns out to be especially important due to the limitations of the database. In a second stage, additional nonparametric methods—in an attempt to be fully consistent—are used to disentangle some reasons as to why productivity differentials might exist. Results show that productivity growth has occurred in most countries, mainly due to improvement in production possibilities. The bootstrap analysis yields further evidence, as for many firms and countries productivity growth, or decline, is not statistically significant. The two-stage analysis provides some additional insights, suggesting that the relevance of environmental variables found in other studies focusing on efficiency could be lessened when focusing on productivity.

Keywords: bank, bootstrap, Malmquist productivity index

JEL Classification: C14, C30, C61, G21, L5

Communications to: Emili Tortosa-Ausina, Departament d'Economia, Universitat Jaume I, Campus del Riu Sec, 12071 Castelló de la Plana, Spain. Tel.: +34 964387163, fax: +34 964728591, e-mail: `tortosa@uji.es`

*Carmen Murillo and José M. Pastor would like to thank the financial support from Ministerio de Educación y Ciencia, BEC2001-1121 and SEC2002-03375 respectively. Emili Tortosa-Ausina acknowledges the financial support of the Generalitat Valenciana (GV01-129) and the Ministerio de Educación y Ciencia (SEC2002-03651). The autors wish to thank Paul W. Wilson and an anonymous referee for their useful comments and suggestions.

[†]Universidad de Cantabria.

[‡]Universitat de València and IVIE.

[§]Universitat Jaume I and IVIE.

1. Introduction

The turmoil which has been affecting the European banking industry over the last two decades or so still seems far from over. Although the main deregulatory initiatives took place in the eighties, in recent years many other issues, such as the growing number of mergers and acquisitions, the final disappearance of banks which have been in trouble for years, etc., have contributed significantly to reshaping European Union (EU) banking industries, and whose impact on firms' efficiency and productivity deserves a renewed evaluation.

Although the number of studies devoted to the analysis of bank efficiency and productivity has been growing rapidly of late, the attention devoted to international comparisons has been much scarcer. This gap has been partially plugged in recent times. For example, the study by Casu *et al.* (2004) undertakes a comparison of parametric and nonparametric techniques for studying productivity in European banking. Focusing on productivity change is relevant since a major problem with efficiency studies is that the analyst may end up without learning whether efficiency improves or deteriorates over time if efficiency is measured with respect to a year-specific frontier. This would need an investigation into the frontier shifted during the sample period. Färe *et al.* (1994b) provide a means of doing so.

However, some of the results obtained by Casu *et al.* (2004) are "mixed", and they conclude that "there is a need for further empirical work in the area of productivity change using various methodological approaches". Our study does exactly that. More specifically, it aims to improve results generated by nonparametric techniques when estimating productivity growth by considering a bootstrap methodology which allows hypotheses testing in the context of Data Envelopment Analysis (DEA). Hence, one of the main drawbacks attributable to nonparametric techniques, i.e., that consisting of their inability to disentangle inefficiency from random error, would wane, contributing significantly to our understanding of catching up (or efficiency change), technical change, and productivity growth (or decline) in the European Union banking sector.

This point is of paramount relevance when examining in depth the underpinnings of our database. Although it contains the most important institutions in each banking industry, some of them are absent, thereby jeopardizing the reliability of our results. Obviously, previous studies' results on the efficiency and productivity of the banking systems of the European Union could be jeopardized in the same way. The present study contributes to addressing this shortcoming thanks to the methodology we employ, whose resampling features are greatly appreciated when there are missing data for some firms. In such a case, bootstrapping, or resampling, techniques become much more informative than in other circumstances in which the whole sample is available, granting us the possibility of conducting statistical inference and, therefore, drawing much more painstaking conclusions. This constitutes a further contribution, since applications of bootstrapping techniques are still scarce in the context of activity analysis techniques, needless to say in the context of the productivity of European banks.

The likely contribution is further understood in light of the somewhat arbitrary nature of our sample of financial institutions; although the sample is highly representative, it is composed of the firms for which consistent data could be collected over the period.[1] Consequently, the results could

[1] This assertion parallels one of the claims by Färe *et al.* (1994b) in their study on the productivity of 17 *arbitrarily*

be different if a different sample were used. Thus, if productivity growth, or decline, is found to be significant for a firm, then if we took another similar batch we should find a similar result; whence we may conclude that this technique turns out to be particularly adequate for the data at hand.

We also improve previous studies by extending the database to a larger number of countries. Although the study by Casu *et al.* (2004) focuses on the largest European Union countries, both in demographic and economic terms, namely, France, Germany, Italy, Spain, and the United Kingdom, our study considers a much broader database in terms of nations, as we consider all EU members with the exception of Greece,[2] constituting therefore a database of 14 countries. The ten new members who joined the EU in 2004 were not included. Finally, our years of study are also of interest, covering the recent period 1995–2001.

We also make an attempt to disentangle some of the sources of the differentials found among productivity indices for European banks. In particular, we explore whether financial markets' integration might be playing a role when measuring productivity growth. We consider whether country effects, physical-neighbor effects, or the year in which each country joined the EU might bias the results achieved for productivity change. In general, these ideas are related to the question of why EU financial markets are so segmented, which is still highly intriguing, both on the supply (savings behavior) and the demand (the behavior of firms) sides. To this end, and in an attempt to maintain consistency, we consider nonparametric methods, as opposed to most previous studies which analyze the likely determinants of efficiency or productivity using either Ordinary Least Squares (OLS) or censored regression models—therefore leading to a certain inconsistency, as nonparametric methods are used in the first-stage of their analysis, and parametric methods in the second stage.

The paper begins with a review of the relevant literature on international comparisons of bank efficiency and productivity (Section 2). Next (Section 3) we present the methodology to compute productivity change and the bootstrap. The following section (Section 4) presents data and defines inputs and outputs. Finally, Section 5 details the most relevant results, along with some ideas about the likely impact of country-specific related variables on productivity.

2. Literature review

The literature on international comparisons of bank efficiency and productivity has, among others, two distinct features (see Table 1). First, the number of existing studies is relatively low, at least when compared with the plethora of bank efficiency studies confined to a single country (Berger and Humphrey, 1997). Second, the number of studies using either parametric—mostly using the Stochastic Frontier Approach (SFA) or the Distribution Free Approach (DFA)—or nonparametric methods—chiefly Data Envelopment Analysis (DEA)—is roughly equal.

selected OECD countries.

[2]Note that we do not differentiate between the EU and Europe. Furthermore, the notion EU refers to the EU-15, not the enlarged EU. In our particular setting, we will speak about EU-14 since Greece was not considered.

Table 1: Literature review

Authors	Indicators[b]	Approach[a] DEA	SFA	DFA	Other	Countries	Period	International	Productivity	Bootstrap
Alam (2001)	EC, TC, TFP	DEA			Malmquist	USA	1980-1989		YES	
Allen and Rai (1996)	CE	DEA	SFA			15 developed countries	1988–1992	YES		
Altunbaş and Chakravarty (2001)	CE		SFA			Europ.countries (not specified)	1994	YES		
Altunbaş and Molyneux (1996)	ES				OLS	4 European countries	1988	YES		
Altunbaş *et al.* (2001)	CE		SFA			15 European countries	1989–1997	YES		
Altunbaş *et al.* (1999)	TC		SFA			15 European countries	1989–1996	YES		
Asmild *et al.* (2004)	EC, TC, TFP	DEA				Canada	1981–2000		YES	
Avkiran (2000)	EC, TC, TFP	DEA			Malmquist	Australia	1986–1995		YES	
Bauer *et al.* (1993)	CE, TFP				Pool, panel and TFA	USA	1977–1988		YES	
Berg *et al.* (1993)	TE	DEA				3 Nordic countries	1992–1993	YES		
Berg *et al.* (1995)	TE	DEA			Malmquist	4 Nordic countries	1992–1993	YES	YES	
Berg *et al.* (1992)	TE	DEA			Malmquist	Norway	1980–1989		YES	
Bergendahl (1995)	TE	DEA			Window analysis	3 Nordic countries	1992–1993	YES		
Berger *et al.* (2000)	CE, PE			DFA		5 OECD countries	1992–1997	YES		
Bikker (1999)	CE		SFA			9 European countries	1989–1997	YES		
Bikker (2002)	CE		SFA			15 European countries	1990–1997	YES		
Bonin *et al.* (2005)	CE, PE	SFA				11 transition countries	1996–2000	YES		
Bos and Schmiedel (2003)	CE, PE		SFA			8 European countries	1993–2000	YES		
Canhoto and Dermine (2003)	TE, SE, TC, TEC, TFP.	DEA			Malmquist	Portugal	1990–1995		YES	
Carbó *et al.* (2003)	TC				AF	13 European countries	1989–1996	YES		
Casu and Girardone (2002)	CE, PE	DEA	SFA			5 European countries	1993–1997	YES		
Casu and Molyneux (2003)	TE	DEA				5 European countries	1993–1997	YES		
Casu *et al.* (2004)	TE, SE, TC, TEC, TFP	DEA			Malmquist, TFA	5 European countries	1994–2000	YES	YES	
Casu and Girardone (2004)	CE, PE, AE, TE	DEA	SFA			Italy	1996–1999	YES		
Cavallo and Rossi (2001)	CE, SEC, SCOPE		SFA			6 European countries	1992–1997	YES		
Cavallo and Rossi (2002)	CE		SFA			6 European countries	1992–1997	YES		
Chaffai *et al.* (2001)	TFP	DEA			Malmquist	3 European countries	1993–1997	YES		
Devaney and Weber (2000)	EC, SE, TC, TFP	DEA			Malmquist	USA	1990–1993		YES	
Dietsch and Lozano-Vivas (2000)	CE			DFA		2 countries (France and Spain)	1988–1992	YES		
Fecher and Pestieau (1993)	CE			DFA		11 OECD countries	1971–1986	YES		
Ferrier and Hirschberg (1997)	TE	DEA				Italy	1986			YES
Fries and Taci (2005)	CE	SFA				15 Eastern European countries	1994–2001	YES		
Fukuyama (1995)	EC, TC, TFP	DEA			Malmquist	Japan	1989–1991		YES	
Fukuyama and Weber (2002)	EC, TC, TFP	DEA			Russell	Japan	1992–1996		YES	
Gilbert and Wilson (1998)	EC, TC, TFP	DEA				Korea	1980–1994		YES	YES
Grifell-Tatjé and Lovell (1996)	EC, TC, TFP	DEA			Malmquist	Spain	1986–1993		YES	
Grifell-Tatjé and Lovell (1997)	EC, TC, TFP	DEA			Malmquist	Spain	1986–1993		YES	
Lozano-Vivas *et al.* (2001)	TE	DEA				10 European countries	1993	YES		
Humphrey (1992)	TFP				GA, Econometric	USA	1968–1987		YES	
Isik and Hassan (2003a)	EC, TC, TFP	DEA			Malmquist	Turkey	1970–1990		YES	
Isik and Hassan (2003b)	EC, PEC, SE, TC, TFP	DEA			Malmquist	Turkey	1992–1996		YES	
Kasman *et al.* (2005)	CE, PE		SFA			16 Latin American countries	1996–2001	YES		
Lozano-Vivas *et al.* (2001)	TE	DEA				10 European countries	1993	YES		
Maggi and Rossi (2003)	CE, SEC, SCOPE			DFA		16 countries (15 European and USA)	1995–1998	YES		
Maudos and Pastor (2000)	CE, PE			DFA		14 European countries	1993–1997	YES		
Maudos and Pastor (2001)	CE, PE		SFA			17 OECD countries	1984–1995	YES		
Maudos *et al.* (2002)	CE, PE			DFA	REM, FEM	10 European countries	1993–1996	YES		
Molyneux (2002)	TC		SFA			15 European countries	1992–2000	YES		
Mukherjee *et al.* (2001)	EC, SE, TC, TFP	DEA			Malmquist	USA	1980–1990		YES	
Noulas (1997)	EC, TC, TFP	DEA			Malmquist	Greece	1991–1992		YES	
Pastor (2002)	TE, TEAR, TEARE, RME	DEA	SFA		Logit, Tobit	4 European countries	1988–1994	YES		
Pastor and Serrano (2005a)	CE	DEA				9 European countries	1992–1998	YES		
Pastor and Serrano (2005b)	CE, PE, RME, CEAR, PEAR			DFA		7 European countries	1993–1997	YES		
Lozano-Vivas *et al.* (2002)	TE	DEA				10 European countries	1993	YES		
Pastor *et al.* (1997)	TE, PTE, SE, TC, TEC, TFP	DEA			Malmquist	8 OECD countries	1992	YES		
Schure *et al.* (2004)	TE				RTFA	15 European countries	1993–1998	YES		
Stavárek (2003a)	TE	DEA				6 European countries	2000–2001	YES		
Stavárek (2003b)	TE	DEA				4 European countries	1994–2001	YES		
Stiroh (2000)	TFP				Pool and panel analysis	USA	1991–1997		YES	
Tirtiroglu *et al.* (1998)	TFP				Törnqvist index	USA	1946–1995		YES	
Tortosa-Ausina *et al.* (2003)	TE, EC, TC, TFP	DEA				Spain	1992–1998		YES	YES
Tsionas *et al.* (2003)	EC, TC, TFP	DEA			Malmquist	Greece	1993–1998		YES	
Vander Vennet (2002)	CE, PE		SFA			17 European countries	1995–1996	YES		
Weill (2003a)	CE		SFA			17 European countries	2000	YES		
Weill (2003b)	CE		SFA			2 European countries	1997	YES		
Weill (2004)	CE	DEA	SFA	DFA		5 European countries	1992–1998	YES		
Wheelock and Wilson (1999)	EC, TC, TFP	DEA			Malmquist	USA	1980–1993		YES	YES
Williams (2004)	CE, PE		SFA			6 European countries	1990–1998	YES		
Williams and Gardener (2003)	CE		SFA			6 European countries	1990–1998	YES		
Worthington (1999)	EC, TC, TFP	DEA			Malmquist	Australia	1993–1997		YES	

[a] DEA: Data Envelopement Analysis; SFA: Stochatic Frontier Approach; DFA: Distribution Free Approach, TFA: Thick Frontier Approach, AF: Average Function, REM: Random Effects Model, FEM: Fixed Effects Model, GA: Growth Accounting; RTFA: Recursive Thick Frontier Approach.

[b] TE: Technical Efficiency; CE: Cost Efficiency; AE: Allocative Efficiency; PE: Profit Efficiency; SE: Scale Efficiency; TC: Technical Change; EC: Efficiency Change; TFP: Total Factor Productivity; CEAR: Cost Efficiency Adjusted by Risk; PEAR: Profit Efficiency Adjusted by Risk; TEAR: Technical Efficiency Adjusted by Risk; TEARE: Technical Efficiency Adjusted by Risk and Environment; RME: Risk Management Efficiency; SEC: Scale Economies; SCOPE: Scope Economies.

2.1. Previous literature on international comparisons of bank efficiency

International comparisons of bank efficiency using nonparametric methods were until recently confined to those by Berg *et al.* (1993) and Bergendahl (1995). In both cases, DEA was used to measure the efficiency of the Nordic banking industries. More recently, Lozano-Vivas *et al.* (2001) and Lozano-Vivas *et al.* (2002) also applied nonparametric techniques to compare technical efficiency in ten European banking industries for 1993, correcting for environmental variables. Pastor (2002) also used DEA to analyze risk management efficiency and the efficiency adjusted by the risk and environment in four European banking systems in the 1988–1994 period. Similarly, Stavárek (2003a,b) used DEA to analyze the technical efficiency of four and six European countries during 2000–2001 and 1994–2001 periods, respectively. Casu and Molyneux (2003) measure technical efficiency for five European countries during the 1993–1997 period, and also analyze also their determinants. Finally, Pastor and Serrano (2005a) analyze cost efficiency for nine European countries over the 1992–1998 period, isolating the inefficiency entirely attributable to specialization.

Other studies have considered the Distribution Free Approach (DFA) to perform international comparisons of bank efficiency. Fecher and Pestieau (1993) compare the cost efficiency of eleven OECD countries for the 1971–1986 period. Likewise, Allen and Rai (1996) used DFA and SFA to estimate cost efficiency in fifteen OECD countries for the 1988–1992 period. On the other hand, Berger *et al.* (2000) address the causes, consequences, and implications of the cross-border consolidation of financial institutions by estimating cross-border banking cost and profit efficiency. Likewise, Dietsch and Lozano-Vivas (2000) investigate the influence of environmental conditions on the cost efficiency of French and Spanish banking industries during 1988–1992. Maudos and Pastor (2000) also use DFA to estimate the cost and profit efficiency of fourteen European banking systems during the 1993–1997 period, taking into account how specialization may bias efficiency. Using a random effects model and a fixed effects model, together with DFA, Maudos *et al.* (2002) analyze both cost and profit efficiency for a sample of ten European Union countries for the 1993–1996 period, finding that profit efficiency levels are much lower than cost efficiency levels. They also examine several likely sources of efficiency differences. Maggi and Rossi (2003) investigate cost efficiency, along with scale and scope economies, for a sample of commercial banks in fifteen European countries and the U.S. during the 1995–1998 period, and test the stability and the robustness of their results across different specifications. Finally, Pastor and Serrano (2005b) analyze risk-adjusted cost and profit efficiency measures for a set of European banking systems using DFA. They find that adjusting for risk is important, especially in the case of profit efficiency.

Finally, a third group of relatively recent papers use the Stochastic Frontier Approach (SFA) to make an international comparison of bank efficiency. Apart from the aforementioned paper by Allen and Rai (1996), Bikker (1999) estimates cost efficiency measures for nine European banking systems over the 1982–1997 period, focusing on the treatment of the differences of efficiency among countries attributable to the heterogeneity of the sample. Likewise, Altunbaş and Chakravarty (2001) use SFA to compare the results yielded by the translog and Fourier specifications for a sample of European banks, showing that the goodness-of-fit criterion is an unreliable indicator of forecasting ability. Altunbaş *et al.* (2001) applied the Fourier functional form and SFA to estimate scale economies, X-inefficiencies and technical change for a sample of banks across fifteen European countries between 1989 and 1997. Maudos and Pastor (2001) analyze cost and profit efficiency for a sample of sixteen countries (fourteen from the European Union, Japan and the US) showing that, since the early 1990s, increased competition has led to profit efficiency gains in the USA and Europe, but not in Japan. In the same way, Cavallo and Rossi (2001, 2002), using SFA also, analyze the cost efficiency of a sample of six OECD countries during 1992-1997. The results confirm that recent regulatory changes have contributed to an increase in the optimal scale. Likewise, Bikker (2002), using SFA, seeks to discover the level and spread of bank cost efficiency in 15 European Union member countries, and finds large spreads in inefficiencies and cost levels across countries and individual banks. Vander Vennet (2002) analyzes the cost and profit efficiency of European financial conglomerates and universal banks from seventeen European countries, finding that conglomerates are more revenue efficient than their specialized competitors, and that the degree of both cost and profit efficiency is higher in universal than in non-universal banks. Molyneux (2002) examines the impact of technical change on cost and profits of a sample of fifteen European countries during the 1992–2000 period and concludes that technical change has reduced total cost of European banks at an average rate of 3.8% per year, while it has reduced profit by 0.45% per year. Bos and Schmiedel (2003) deal with the dilemma of common frontier vs. separated frontiers, constructing the so-called metafrontiers. Using a data set of more than 5,000 large commercial banks from eight European banking markets over the 1993–2000 period, they conclude that traditional efficiency techniques based on pooled frontier efficiency scores tend to underestimate cost and profit efficiency levels, resulting in biased cross-country comparisons.

More recently, other studies have set out to analyze the performance of Eastern banking systems. For instance, Weill (2003a) compares the efficiency of banks from 17 Western European countries and six Eastern European countries to assess the performance gap between the two groups and also tests the possible influence of environmental variables and risk preferences on the efficiency gap. The results reveal a gap in bank efficiency between Eastern and Western European countries. In another study, Weill (2003b) compares the performance of foreign-owned and domestic-owned banks operating in the Czech Republic and Poland, using several approaches (DEA, SFA and DFA) and concludes that, on average, foreign-owned banks are more efficient than domestic-owned banks. Bonin *et al.* (2005) investigate the effects of ownership on bank efficiency for eleven transition countries for the 1996–2000 period, finding that foreign-owned banks are more cost-efficient than other banks. Similarly, Fries and Taci (2005) analyze cost efficiency for 15 Eastern European countries, finding that private banks are more efficient than state-owned banks. Williams (2004) analyzes the management and the cost and profit efficiency for savings banks in six European countries between 1990 and 1998, suggesting that the most pressing problem for European saving banks is bad management. Finally, Schure *et al.* (2004) assess the efficiency of the European banking sector in the 1993–1997 period for banking systems of fifteen European countries using the new recursive thick frontier approach (RTFA), finding that X-inefficiency is the main source of bank inefficiency in the EU and efficiency levels are heterogeneous within Europe, and there seems to be no tendency towards convergence.

2.2. International comparisons of Total Factor Productivity (TFP) growth in banking

Since the early nineties, a number of studies have used parametric approaches to estimate either Total Factor Productivity (TFP) growth and/or technological change. There are different approaches to measure TFP growth and the differences come from the approach taken to estimate the weight to value the multiple inputs and outputs. Lately, most studies tend to use frontier approaches—parametric or nonparametric—instead of the traditional econometric Solow approach, mainly because the use of average functions ignores the existence of inefficiency in the behavior of banking companies.[3] The underlying problem is that this approach, only valid under the assumption of technical and allocative efficiency, results in biased estimation when inefficiency is present. In addition, this methodology cannot decompose the TFP growth of each banking firm into its technical change and efficiency change components.

In order to overcome this drawback, recent studies have used frontier approaches to explicitly consider that efficiency change is an important component of productivity growth. The overwhelming majority use DEA and the Malmquist productivity index (MPI)[4] to examine productivity growth, efficiency change, and technical progress. Accordingly, Worthington (1999) and Avkiran (2000), using MPI, analyze productivity growth in deposit-taking institutions and four major trading banks and six regional banks respectively in Australia. Similarly, Noulas (1997) and Tsionas *et al.* (2003) use MPI to investigate productivity growth in the Greek banking industry. Fukuyama (1995) and Fukuyama and Weber (2002) examined the efficiency and productivity growth in the Japanese banking industry for the 1989–1991 and 1993–1996 periods, respectively. Gilbert and Wilson (1998) use MPI and bootstrapping techniques to analyze and decompose the productivity growth of Korean banks over the 1980–1994 period. Casu and Girardone (2004) evaluate productivity change for Italian financial conglomerates over the 1996–1999 period using both parametric and nonparametric approaches. Canhoto and Dermine (2003) quantify the magnitude of efficiency gains and TFP growth of Portuguese banks over the 1990–1995 period. We must pay special attention to the study by Berg *et al.* (1992), since it was the first one to use MPI in an analysis of productivity growth during the deregulation of the Norwegian banking industry (1980–1989). For the Spanish case, Grifell-Tatjé and Lovell (1996, 1997) analyze the sources of productivity growth for Spanish savings banks over the 1986–1993 period. More recently, Tortosa-Ausina *et al.* (2003) calculate the productivity growth for Spanish savings banks over the post-deregulation period (1992–1998) using MPI and bootstrapping techniques. Isik and Hassan (2003a,b) measure the efficiency and productivity of the Turkish banking sector for the 1992–1996 and 1970–1990 periods, respectively. Wheelock and Wilson (1999), Alam (2001), Mukherjee *et al.* (2001), Devaney and Weber (2000) use MPI to analyze productivity growth for US banks.

However, all these studies focus on the analysis of particular banking systems. Those devoted to international comparisons of banking productivity are much fewer—just two. First, Berg *et al.* (1995) use MPI to analyze the productivity growth of the banking systems in four Nordic countries.

[3] See, for example, Bauer *et al.* (1993), Humphrey (1992, 1993), Tirtiroglu *et al.* (1998) and, more recently, Stiroh (2000).

[4] Grosskopf (2003) reviews some ideas about the Malmquist productivity index and points out that, in fact, the index was not suggested by Sten Malmquist himself but by Caves *et al.* (1982).

However the most recent contribution on this issue is the study by Casu *et al.* (2004), who use MPI and parametric techniques to analyze productivity change for five European Union countries during the 1994–2000 period.[5]

Unfortunately, both DEA and the parametric approaches to estimate efficiency and productivity share a common weakness: it is difficult to determine the statistical precision of the results. In the case of the parametric approaches this is due to the highly nonlinear way in which efficiency scores are calculated from the overall estimates. In the DEA case, because the method is nonparametric and therefore the distribution of the efficiency measure is neither known nor specified (Ferrier and Hirschberg, 1997). Therefore, the absence of an indicator of statistical significance reduces the reliability and usefulness of the results.

Some authors have used bootstrapping techniques to construct confidence intervals for efficiency scores and productivity indices in order to address the main shortcoming of the DEA-MPI approach. Early initiatives date to Ferrier and Hirschberg (1997), who measured technical efficiency in Italian banks for 1986. Regarding productivity change, there are only three studies that combine MPI and bootstrapping techniques. The first is by Gilbert and Wilson (1998), who analyzed the effects of deregulation on the productivity of Korean Banks over the 1980–1994 period. The second is that by Wheelock and Wilson (1999), who analyzed productivity change in the U.S. banking industry over 1984–1993. More recently, Tortosa-Ausina *et al.* (2003) analyze the productivity growth of Spanish savings banks over the 1992–1998 period.

In short, out of those approximately forty studies (see Table 1) into international comparisons of bank efficiency, parametric and nonparametric techniques are used in similar proportions. Regarding the analysis of productivity growth in banking, only two of the reviewed studies analyze productivity growth at the international level, and none of them uses bootstrapping to address the problem of statistical significance. Therefore, our study constitutes the first attempt to analyze banking productivity for a large set of banking systems using bootstrap techniques.

3. Methodology

As we will see in this Section, the Malmquist index identifies productivity growth with respect to two time periods by means of a quantitative ratio index of distance functions. To work out this type of distance functions, we have to distinguish inefficient units from efficient ones by a production frontier estimation. As we have previously explained, DEA relies on two major assumptions: firstly, the data provide us with a good approximation to the production function. Secondly, there is no allowance for a stochastic error term.[6] Thus, this method considers the observed data as the real values of the production function. Since DEA is a deterministic method, its main disadvantage is the lack of statistical properties of its estimates due to the fact that the random structure of the model

[5]Other studies, instead of analyzing productivity change over time, compare the productivity differences among various countries. In this line, Pastor *et al.* (1997) use MPI to analyze productivity, technology and efficiency differences for eight industrialized countries for year 1992. Likewise, Chaffai *et al.* (2001) use a Malmquist type productivity index to explain productivity gaps among four European countries.

[6]However, these assumptions are far less restrictive than the requirements demanded by parametric methods such as SFA.

does not discriminate between inefficiency and other sources of randomness. When this detriment was addressed by some researchers, Sengupta (1982) began to look at stochastic issues, although the statistical foundation of the DEA estimator was provided by Simar (1992) and Banker (1993). Notwithstanding Korostelev *et al.* (1995) established the consistency of the DEA estimator in the single input case, and Kneip *et al.* (1998) analyzed the convergence of the DEA estimator for the multi- input, multi-output framework. However, the difficulty was greater when, in order to construct confidence intervals, the aim was to obtain the asymptotic distribution of the efficiency. Gijbels *et al.* (1999) obtained their sampling distribution for one input and one output. In the case of the multi-input multi-output setup, Simar and Wilson (1998b) designed a bootstrap mechanism to conduct inference in DEA and, more recently, Kneip *et al.* (2003) have obtained the asymptotic distribution of efficiency. However, since it does not possess an analytical form the only feasible alternative still appears to be either the bootstrap or the subsampling methods.

With regard to the MPI, the lack of statistical properties of the efficiency also applies, since DEA estimates are mere components of the index. Therefore, in an attempt to solve the previous problem in the productivity framework, Simar and Wilson (1998a, 1999) modified the bootstrap procedure for technical efficiency so as to enable distinguish between significant and nonsignificant changes in productivity. In the next section we will first introduce a brief review of both efficiency measurement and bootstrap procedure and, second, apply them to the productivity analysis.

3.1. Bootstrapping DEA Estimates

We consider that N banking firms, at time t, produce q outputs from p inputs which, following Simar and Wilson's (1998b) notation, define the feasible set of input-output combinations as follows:

$$\Psi = \{(\boldsymbol{x}, \boldsymbol{y}) \in \mathbb{R}^{p+q} \mid \boldsymbol{x} \text{ can produce } \boldsymbol{y}\}. \tag{1}$$

For any $\boldsymbol{y} \in \mathbb{R}^q_+$ we may define the previous set by the input requirement set defined as,

$$X(\boldsymbol{y}) = \{x \in \mathbb{R}^p_+ \mid (\boldsymbol{x}, \boldsymbol{y}) \in \Psi\}. \tag{2}$$

The input efficient frontier may be defined by the following subset of $X(\boldsymbol{y})$:

$$\delta X(\boldsymbol{y}) = \{\boldsymbol{x} \in X(\boldsymbol{y}) \mid \theta\boldsymbol{x} \notin X(\boldsymbol{y}) \quad \forall \quad 0 < \theta < 1\}, \tag{3}$$

Then, efficiency measures for each firm (Farrell, 1957) are calculated relative to this frontier as the following distance function,

$$\theta(\boldsymbol{x}, \boldsymbol{y}) = \inf\{\theta \mid \theta\boldsymbol{x} \in X(\boldsymbol{y})\} \tag{4}$$

$\theta(\boldsymbol{x}, \boldsymbol{y})$ defines the input technical efficiency (the maximum contraction) along a fixed ray away from the efficient input. A value of $\theta(\boldsymbol{x}, \boldsymbol{y}) = 1$ means that the producer is input efficient while a value of $\theta(\boldsymbol{x}, \boldsymbol{y}) \leq 1$ indicates an inefficient producer who may reduce all the inputs in that proportion.

Since Ψ, $X(\boldsymbol{y})$ and $\delta X(\boldsymbol{y})$ are unknown, Equation (4) implies that $\theta(\boldsymbol{x}, \boldsymbol{y})$ is also unidentified. The estimation of efficiency and the analysis of its resulting accuracy in a nonparametric setup require us to introduce some assumptions on the Data Generating Process (DGP). In other words, from an unknown population, we have to identify the distribution function from which to draw random samples similar to the same as $X = \{(\boldsymbol{x}_j, \boldsymbol{y}_j)\}_{j=1}^{N}$, where $j = 1, \ldots, N$ is the number of banking firms. The selection of DEA as the estimation method for efficiency requires the incorporation of some assumptions for both the production possibility set (mainly convexity and free disposability of inputs and outputs) and the distance function (see Färe *et al.*, 1994a), as well as some regularity assumptions on the DGP (Kneip *et al.*, 1998). Under these assumptions, the DEA consistently estimates the production set $(\widehat{\Psi})$ as:

$$\widehat{\Psi} = \{(\boldsymbol{x}, \boldsymbol{y}) \in \Re_{+}^{p+q} |\ \boldsymbol{x} \geq \sum_{j=1}^{N} \boldsymbol{\gamma}_j \boldsymbol{x}_j \quad \boldsymbol{y} \leq \sum_{j=1}^{N} \boldsymbol{\gamma}_j \boldsymbol{y}_j \quad \forall \boldsymbol{\gamma}_j \geq 0\}, \tag{5}$$

where $\boldsymbol{\gamma}_j$ is the intensity vector of firm j and it defines its *best practice* or *benchmark firm* by a linear combination of all the firms observed in the sample. Constraint $\boldsymbol{\gamma}_j \geq 0$ imposes the assumption of constant returns to scale into the benchmark technology while the first two constraints in Equation (5) imply that excess of outputs or inputs can be disposed of freely.

The DEA estimates of equations (2) and (3) are then,

$$\widehat{X}(\boldsymbol{y}) = \{\boldsymbol{x} \in \mathbb{R}_{+}^{p} \mid (\boldsymbol{x}, \boldsymbol{y}) \in \widehat{\Psi}\}, \tag{6}$$

and

$$\delta \widehat{X}(\boldsymbol{y}) = \{\boldsymbol{x} \in \widehat{X}(\boldsymbol{y}) \mid \theta \boldsymbol{x} \notin \widehat{X}(\boldsymbol{y}) \quad \forall \quad 0 < \theta < 1\}. \tag{7}$$

while the estimation of the Farrell technical efficiency measure is computed by linear programming techniques as follows

$$\widehat{\theta}(\boldsymbol{x}_j, \boldsymbol{y}_j) = \min\{\theta \mid \sum_{j=1}^{N} \gamma_j \boldsymbol{x}_j \leq \theta \boldsymbol{x}_j \quad \boldsymbol{y}_j \leq \sum_{j=1}^{N} \gamma_j \boldsymbol{y}_j \quad \forall \gamma_j \geq 0\}. \tag{8}$$

The properties of $\widehat{\theta}(\boldsymbol{x}_j, \boldsymbol{y}_j)$ depend on the unknown distribution function from which random samples can be drawn; moreover, the accuracy of the estimation requires a knowledge of the distribution function of the estimator, or at least its mean and variance. Efron (1979) introduced the idea of approximating the unknown population distribution function F by its empirical distribution F_N ("plug-in estimation" or "analogy principle") and therefore, $\theta = t(F)$ might be estimated by following the same principle by $\widehat{\theta} = t(F_N)$. This is the bootstrap distribution and is approximated by Monte Carlo simulations provided that, first, the variability of the efficiency when sampling from F comes close to the statistic variability when resampling from F_N and, second, it is allowed to draw any values for the statistic by resampling from F_N. Thus the resampling procedure will allow for bootstrap samples $X^* = \{(\boldsymbol{x}_j^*, \boldsymbol{y}_j^*)\}_{j=1}^{N}$ similar to the original data $X = \{(\boldsymbol{x}_j, \boldsymbol{y}_j)\}_{j=1}^{N}$.

In the efficiency framework, Simar and Wilson (1998b)[7] proposed the homogeneous bootstrap

[7] Simar and Wilson's procedure has proved capable of solving the inconsistent problems of other applications such as the use of a naive bootstrap; moreover it has solved the absence of probability mass beyond the upper bound of efficiency by Silverman's (1986) reflection method.

procedure[8] for generating B samples as $X^* = \{(\boldsymbol{x}_j^*, \boldsymbol{y}_j^*)\}_{j=1}^N$ by mimicking the DGP defined above (see Simar and Wilson, 2000b, for a complete description of the algorithm) and for each firm and for each of these B samples, the bootstrap value of efficiency can be estimated using DEA as:

$$\widehat{\theta}^*(\boldsymbol{x}_j, \boldsymbol{y}_j) = \min\{\theta \mid \sum_{j=1}^{N} \boldsymbol{\gamma}_j \boldsymbol{x}_j^* \leq \theta x_j \quad \boldsymbol{y}_j \leq \sum_{j=1}^{N} \boldsymbol{\gamma}_j y_j^* \quad \forall \boldsymbol{\gamma}_j \geq 0\}. \tag{9}$$

Thus, we obtain the empirical distribution for each firm as $\{\widehat{\theta}_b^*(\boldsymbol{x}_j, \boldsymbol{y}_j)\}_{b=1}^B$, and its sample mean $B^{-1}\sum_{b=1}^{B} \widehat{\theta}_b^*(\boldsymbol{x}_j, \boldsymbol{y}_j)$ could be used as an estimator of the efficiency. Since by construction $\widehat{\Psi} \subseteq \Psi$, the estimator $\widehat{\theta}(\boldsymbol{x}_j, \boldsymbol{y}_j)$ is a downward-biased estimator of $\theta(\boldsymbol{x}_j, \boldsymbol{y}_j)$ hence $B^{-1}\sum_{b=1}^{B} \widehat{\theta}_b^*(\boldsymbol{x}_j, \boldsymbol{y}_j)$ will be a downward-biased estimator of $\widehat{\theta}(\boldsymbol{x}_j, \boldsymbol{y}_j)$.

The bias is then determined as: $\widehat{bias} = B^{-1}\sum_{b=1}^{B} \widehat{\theta}_b^*(\boldsymbol{x}_j, \boldsymbol{y}_j) - \widehat{\theta}(\boldsymbol{x}_j, \boldsymbol{y}_j)$, and confidence intervals for the efficiency of each firm can be estimated via the percentile confidence interval by the following value,

$$\left(\widehat{\theta}^*(\boldsymbol{x}_j, \boldsymbol{y}_j)^{(\alpha)}, \widehat{\theta}^*(\boldsymbol{x}_j, \boldsymbol{y}_j)^{(1-\alpha)}\right) \tag{10}$$

where $\widehat{\theta}^*(\boldsymbol{x}_j, \boldsymbol{y}_j)^{(\alpha)}$ represents the $100\alpha^{th}$ percentile of the empirical distribution $\{\widehat{\theta}_b^*(\boldsymbol{x}_j, \boldsymbol{y}_j)\}_{b=1}^B$ once it has been ordered.

3.2. Bootstrapping Malmquist indices

Productivity and efficiency are only equivalent if inputs or outputs are fixed; in a dynamic setup, therefore, a change in technical efficiency might not be an indicator of change in productivity. The measurement of productivity by the MPI was introduced by Caves *et al.* (1982), and it compares, avoiding the discretionary selection of the technology by a geometrical mean, the efficiency of a firm j in periods of time t_1 and t_2 ($t_1 < t_2$), in terms of Farrell's efficiencies as,

$$\widehat{\mathcal{M}}_j(t_1, t_2) = \widehat{\mathcal{M}}_j(\boldsymbol{x}^{t_1}, \boldsymbol{y}_j^{t_1}, \boldsymbol{x}^{t_2}, \boldsymbol{y}_j^{t_2}) = \left(\frac{\widehat{\theta}_{t_1}^{t_1}}{\widehat{\theta}_{t_2}^{t_1}} \times \frac{\widehat{\theta}_{t_1}^{t_2}}{\widehat{\theta}_{t_2}^{t_2}}\right)_j^{1/2} \tag{11}$$

where $\widehat{\theta}_{t_1}^{t_1} = \widehat{\theta}^{t_1}(\boldsymbol{x}_j^{t_1}, \boldsymbol{y}_j^{t_1})$ is estimated as in Equation (8).[9] However $\widehat{\theta}_{t_2}^{t_1} = \widehat{\theta}^{t_1}(\boldsymbol{x}_j^{t_2}, \boldsymbol{y}_j^{t_2})$ is determined by the following relationship,

$$\hat{\theta}^{t_1}(\boldsymbol{x}_j^{t_2}, \boldsymbol{y}_j^{t_2}) = \min\{\theta \mid \sum_{j=1}^{N} \boldsymbol{\gamma}_j \boldsymbol{x}_j^{t_1} \leq \theta \boldsymbol{x}_j^{t_2} \quad \boldsymbol{y}_j^{t_2} \leq \sum_{j=1}^{N} \boldsymbol{\gamma}_j \boldsymbol{y}_j^{t_1} \quad \forall \boldsymbol{\gamma}_j \geq 0\}. \tag{12}$$

and it represents the efficiency estimated for a sample of period t_2 when the frontier is that of period t_1[10].

[8]The homogeneous bootstrap assumes that the efficiency distribution is homogeneous, i.e. the location of firms in the production set and their inefficiency are independent. In contrast, the heterogeneous bootstrap (Simar and Wilson, 2000a) is the most suitable tool in the dependency case but, in the case of large data panels such as ours, is hard to deal with.

[9]Each value of efficiency is estimated under constant returns to scale because the index only correctly measures the productivity change if the true technology exhibits constant returns to scale everywhere (Grifell-Tatjé and Lovell, 1995).

[10]By reversing t_1 and t_2 in Equation 12 we obtain $\widehat{\theta}_{t_1}^{t2}$

A firm j will have improved productivity from t_1 to t_2 when $\widehat{\mathcal{M}}_j(t_1, t_2) < 1$; in contrast, an index greater than one will indicate a decrease in productivity; and finally, $\widehat{\mathcal{M}}_j(t_1, t_2) = 1$ will suggest stagnation in productivity; if we had chosen an output oriented approach, interpretations would be reversed.

One of the main advantages of MPI is that it can be rewritten and decomposed into different indices in order to analyze the different sources of change in productivity. One of the simplest decompositions was proposed by Grosskopf (1993), and separates productivity change into changes in efficiency (catching-up) and frontier changes (technical change). Since then, new decompositions have been developed (see Grifell-Tatjé and Lovell, 1999, for a review of these and their properties) and all of them have focused on more exhaustive decompositions of productivity change. However in our paper we have applied the former since its simplicity may constitute a great advantage in terms of significance of results.[11]

The index may be expressed as follows:

$$\widehat{\mathcal{M}}_j(t_1, t_2) = \left[\frac{\widehat{\theta}^{t_1}_{t_1}}{\widehat{\theta}^{t_2}_{t_2}}\right]_j \cdot \left[\left(\frac{\widehat{\theta}^{t_2}_{t_1}}{\widehat{\theta}^{t_1}_{t_1}} \times \frac{\widehat{\theta}^{t_2}_{t_2}}{\widehat{\theta}^{t_1}_{t_2}}\right)^{1/2}\right]_j = \widehat{EC}_j(t_1, t_2) \cdot \widehat{TC}_j(t_1, t_2) \tag{13}$$

The catching-up component ($\widehat{EC}_j(t_1, t_2)$) stands for productivity changes due to a change in the relative efficiency of the firm. The index of technical change ($\widehat{TC}_j(t_1, t_2)$) provides the change of productivity due to the frontier shift. Values for both indices are greater than, less than or equal to unity, and their interpretations are analogous to those provided above for productivity change.

The estimation of the ratios in Equation (13) by DEA only conveys the lack of statistical properties of the efficiency to the indices themselves. In other words, without carrying out the inference analysis we will still not know whether the indices obtained are due to sampling variability or statistically significant results. In order to overcome this drawback, Simar and Wilson (1998a, 1999) adapted the bootstrap procedure explained in the previous section to the Malmquist index. For MPI, the algorithm generates bootstrap efficiencies preserving the temporal correlation of the data by exchanging the univariate function of Section 3.1 for a bivariate kernel density.[12] In practice, the bootstrap procedure for the Malmquist TFP index deviates slightly from that defined for technical efficiency, the main divergence attributable to the resampling procedure: we resample pairs of efficiency values for two consecutive years instead of resampling on the single efficiency values. A necessary consequence derived from sampling in pairs is the requirement to gather complete panel data for the analysis, because, otherwise, the bootstrap would be inconsistent.

The empirical distribution of each index for each firm

$$\left[\widehat{\mathcal{M}^*}_b(t_1, t_2)^j, \widehat{EC^*}_b(t_1, t_2)^j, \widehat{TC^*}_b(t_1, t_2)^j\right]_{b=1}^{B}, \tag{14}$$

[11] A more exhaustive decomposition of MPI, as in Simar and Wilson (1998a), might imply that although changes in productivity might be significant, the sources of productivity could themselves be nonsignificant.

[12] The kernel smoothing estimation was performed following Simar and Wilson (1999) guidelines for bandwidth selection.

is obtained by estimating, as in Equation (9), the efficiencies of the Malmquist index and its decomposed indices from Equation (13) for two consecutive years and by repeating this process B times. As in the previous section, the bias estimator of each change index can be obtained by:[13]

$$\widehat{bias}\{\widehat{\mathcal{M}}_j(t_1,t_2)\} = B^{-1}\sum_{b=1}^{B}\widehat{\mathcal{M}}_b^*(t_1,t_2)^j - \widehat{\mathcal{M}}_j(t_1,t_2), \tag{15}$$

Akin to Equation (10), we will obtain the percentile confidence interval for $\mathcal{M}_j$ as

$$(\widehat{\mathcal{M}}^*(t_1,t_2)^{(\alpha)}, \widehat{\mathcal{M}}^*(t_1,t_2)^{(1-\alpha)})^j. \tag{16}$$

The application for each firm of the above percentile confidence interval provides us with a test of significance for $\widehat{\mathcal{M}}_j(t_1,t_2)$; i.e., since stagnation is suggested by a value equal to one for the index, the presence of the unity in the interval defined in Equation (16) would be interpreted as nonsignificantly different from the unity value for $\widehat{\mathcal{M}}_j(t_1,t_2)$. However, if unity does not belong to the confidence interval, the value of the change in productivity estimated by DEA would be significant.

4. Data

4.1. The sample

International comparisons of efficiency and productivity must select data very carefully. Not only does the possible accounting heterogeneity of the variables used have to be considered, but attention must also be paid to the different specializations and the different environments in which firms operate. In this study, the data base was obtained from Bankscope, which provides homogenous information on banks from different countries, and classifies them in terms of specialization, so that accounting uniformity is guaranteed. Homogenization of specialization was achieved by considering only commercial banks, therefore excluding other categories such as savings banks, state owned banks, industrial and development banks, etc.

The total sample contains annual information for a balanced panel of 3,997 banks between 1995 and 2001 for the 14 European Union countries included in our study. The number of observations for each country (see Table 2) ranges from 21, in the case of Finland, to 882 in the case of France.

[13] We only illustrate the case of the Malmquist productivity index, but the procedure is identical for each component making up the index.

Table 2: Summary statistics on inputs and outputs (pooled data, 1995–2001)

		y_1 ‡	y_2 ‡	y_3 ‡	y_4 ‡	y_5 ‡	x_1 ‡	x_2 ‡	x_3 ‡
AUSTRIA	Median	223.60	334.50	26.90	164.60	4.95	356.15	5.95	7.35
	Mean	709.23	1,098.60	43.38	1,301.50	15.77	1,998.03	14.46	24.19
	Max	5,791.00	7,713.80	216.80	21,736.30	90.20	23,491.20	90.20	180.00
	Min	1.90	39.40	0.00	24.50	0.70	39.40	1.00	0.10
	Std.Dev.	1,187.43	1,650.50	50.39	3,998.37	21.10	4,510.39	20.66	40.25
	# observations	140	140	140	140	140	140	140	140
BELGIUM	Median	466.85	1,314.55	488.65	301.20	11.65	1,386.90	12.25	11.15
	Mean	5,404.16	9,809.75	4,160.57	3,577.39	88.81	12,763.46	101.38	153.56
	Max	55,803.00	110,308.00	41,953.00	32,998.00	1,196.00	123,704.00	1,064.00	1,656.00
	Min	5.10	66.00	4.70	5.20	0.00	66.00	0.60	0.00
	Std.Dev.	13,668.10	23,567.30	10,113.57	8,594.71	230.89	31,217.48	248.44	395.94
	# observations	126	126	126	126	126	126	126	126
DENMARK	Median	149.77	257.77	0.45	93.44	3.32	264.07	6.37	4.95
	Mean	2,010.58	2,121.54	36.60	1,214.16	23.24	3,024.66	33.05	34.66
	Max	125,561.25	87,175.16	1,503.58	67,356.51	1,061.68	183,004.35	1,239.82	918.69
	Min	10.31	32.22	0.00	6.47	0.20	33.48	0.85	0.36
	Std.Dev.	11,285.22	9,354.57	201.92	6,121.85	95.21	16,402.06	119.96	112.79
	# observations	287	287	287	287	287	287	287	287
FINLAND	Median	3,755.20	5,027.50	20.80	4,891.80	66.00	8,568.60	46.00	201.00
	Mean	5,199.65	6,542.50	28.41	4,627.19	77.77	9,849.50	78.93	204.83
	Max	13,988.00	15,096.00	65.00	10,608.60	186.00	25,189.00	191.20	507.00
	Min	394.10	392.10	1.00	194.60	3.70	545.40	9.80	2.70
	Std.Dev.	4,594.73	5,434.36	24.54	3,664.95	65.82	7,933.11	73.16	181.08
	# observations	21	21	21	21	21	21	21	21
FRANCE	Median	402.90	684.39	6.40	286.90	12.90	854.40	15.35	7.10
	Mean	5,893.32	8,634.90	1,387.91	5,277.43	140.56	11,128.61	154.26	137.50
	Max	230,968.00	436,392.00	92,118.00	341,384.00	5,965.00	537,293.00	6,467.00	7,514.00
	Min	0.10	0.40	0.00	0.00	0.00	1.70	0.10	0.00
	Std.Dev.	23,725.00	36,798.58	6,552.92	24,478.03	544.65	46,046.68	614.91	589.89
	# observations	882	882	882	882	882	882	882	882
GERMANY	Median	327.85	646.30	83.00	213.60	5.20	677.50	8.60	3.70
	Mean	1,421.72	2,037.50	440.86	587.53	23.10	2,303.09	24.54	17.47
	Max	25,893.30	30,293.00	16,130.10	11,822.40	504.20	40,963.80	345.00	417.80
	Min	0.10	2.60	0.00	0.00	0.00	2.60	0.60	0.00
	Std.Dev.	3,201.88	3,942.99	1,212.82	1,225.37	57.08	4,766.13	46.71	46.50
	# observations	826	826	826	826	826	826	826	826
IRELAND	Median	5,275.60	7,792.30	1,347.10	1,469.70	18.40	8,269.00	27.80	18.40
	Mean	12,970.14	16,848.91	4,831.63	2,469.83	213.39	19,279.46	229.20	256.87
	Max	57,077.00	67,780.00	24,246.50	8,527.00	1,258.00	74,833.00	1,348.00	1,305.00
	Min	498.60	555.20	60.50	105.20	0.10	940.80	0.60	0.10
	Std.Dev.	16,203.26	19,591.28	6,263.28	2,342.57	351.74	21,872.58	370.65	418.49
	# observations	49	49	49	49	49	49	49	49
ITALY	Median	1,148.10	1,202.30	336.00	288.00	17.40	1,792.70	31.00	29.10
	Mean	6,577.46	6,607.99	1,912.42	1,717.01	116.06	9,703.29	175.43	231.22
	Max	74,452.30	82,183.10	30,100.50	22,369.30	1,890.40	116,291.40	1,817.00	3,094.20
	Min	18.80	18.00	0.10	0.30	0.00	18.00	1.80	0.10
	Std.Dev.	14,205.85	14,783.21	4,216.27	3,878.84	269.94	21,068.59	366.96	535.58
	# observations	343	343	343	343	343	343	343	343
LUXEMBOURG	Median	220.80	1,305.10	121.00	760.30	9.70	1,395.20	5.40	2.50
	Mean	1,024.94	4,092.11	1,174.64	2,455.37	35.60	4,466.24	16.82	20.97
	Max	13,292.90	46,163.20	17,262.20	37,019.20	1,002.90	46,529.70	452.70	503.80
	Min	0.60	20.50	0.00	10.00	0.10	23.10	0.20	0.00
	Std.Dev.	1,821.60	6,347.92	2,366.42	3,970.74	92.74	7,088.07	43.10	58.53
	# observations	455	455	455	455	455	455	455	455
NETHERLANDS	Median	1,285.10	1,956.60	198.10	438.80	7.00	2,077.00	12.60	9.00
	Mean	23,951.77	27,276.48	8,002.60	5,816.96	362.56	34,774.27	454.23	467.68
	Max	349,799.00	420,207.00	142,931.00	74,165.00	6,529.00	508,985.00	7,653.00	7,331.00
	Min	21.20	119.30	0.00	19.80	0.20	119.30	1.40	0.10
	Std.Dev.	63,280.71	77,718.43	24,825.21	16,172.15	1,087.87	94,224.52	1,364.78	1,395.33
	# observations	147	147	147	147	147	147	147	147
PORTUGAL	Median	1,674.75	2,462.90	102.05	630.75	17.05	2,609.85	33.70	74.60
	Mean	4,374.86	6,055.28	478.09	2,099.64	50.53	6,870.24	81.99	135.68
	Max	24,569.20	24,931.40	3,045.10	8,517.40	342.70	35,179.30	320.50	447.90
	Min	92.70	127.70	0.00	153.10	0.10	207.70	1.40	2.10
	Std.Dev.	5,749.11	7,255.21	801.56	2,517.41	76.10	8,536.52	97.50	148.27
	# observations	70	70	70	70	70	70	70	70
SPAIN	Median	661.45	944.00	68.65	212.25	14.90	953.40	17.80	23.95
	Mean	7,276.89	11,283.04	3,750.01	1,982.38	187.77	12,728.75	209.32	348.07
	Max	175,214.91	237,565.30	100,673.70	41,034.10	5,535.20	290,062.30	5,258.30	6,705.50
	Min	0.70	10.70	0.00	0.00	0.00	10.70	0.60	0.00
	Std.Dev.	24,539.34	37,643.01	14,372.72	6,417.30	690.18	43,991.21	714.43	1,171.14
	# observations	308	308	308	308	308	308	308	308
SWEDEN	Median	32,231.50	28,022.63	6,882.59	5,700.71	356.58	41,652.76	362.15	286.54
	Mean	29,171.72	26,211.94	7,604.47	6,912.45	428.06	40,316.92	386.09	381.99
	Max	86,545.58	74,307.02	18,990.88	18,971.34	1,723.51	105,335.95	1,393.44	2,207.95
	Min	599.68	1.64	2.87	16.93	0.36	1,627.10	1.74	13.63
	Std.Dev.	26,774.13	21,585.40	6,302.41	5,771.38	395.92	34,477.65	351.61	407.43
	# observations	35	35	35	35	35	35	35	35
UK	Median	877.21	1,484.02	147.16	814.26	17.45	1,750.74	21.46	16.49
	Mean	15,900.92	21,601.01	5,603.76	7,584.20	400.19	26,480.24	365.19	401.21
	Max	301,542.21	380,474.21	106,240.50	123,571.22	6,949.73	462,694.29	6,115.37	7,280.51
	Min	1.43	24.94	0.00	0.66	0.32	28.32	0.93	0.00
	Std.Dev.	41,000.03	54,972.66	16,672.87	18,792.77	1,087.54	65,747.86	988.87	1,140.79
	# observations	308	308	308	308	308	308	308	308
Total	Median	438.90	829.03	64.30	324.70	9.60	955.20	11.72	7.50
	Mean	5,800.24	7,973.06	1,979.94	3,061.36	121.12	10,023.99	131.17	149.24
	Max	349,799.00	436,392.00	142,931.00	341,384.00	6,949.73	537,293.00	7,653.00	7,514.00
	Min	0.10	0.40	0.00	0.00	0.00	1.70	0.10	0.00
	Std.Dev.	22,905.90	31,087.29	8,939.46	13,654.07	512.63	38,265.64	546.27	639.06
	# observations	3,997	3,997	3,997	3,997	3,997	3,997	3,997	3,997

‡In thousands of euros.

4.2. Inputs and outputs

We have selected the intermediation approach (as opposed to the production approach) for measuring bank output, which considers firms as primarily intermediating funds between savers and investors. This issue is often convoluted with the definition of bank output, for which three different methods exist, namely, the asset, user cost, and value-added approaches (Berger and Humphrey, 1992). Some data limitations underlie the usual preference for the asset approach, and our study is by no means an exception. Yet we try to be more comprehensive, taking into account that some deposits have output features, as well as other outputs accounting for the nontraditional activities most banks are currently engaged in (Allen and Santomero, 1998, 2001; Rogers and Sinkey Jr, 1999) and which may influence efficiency (Rogers, 1998).

Accordingly, as there is a broad consensus over the inputs' choice, our selection is free from controversy. Specifically, it encompasses labor (x_1), measured by total labor expenses; capital (x_2), measured by physical capital; and borrowed funds (customer and short term funding, and other funding, x_3); the last category is important since it generates roughly two thirds of total bank costs.

The output choice consists of five categories. The first is customer loans (y_1), defined as all forms of loans performed by banks. This is virtually the only asset category unanimously treated as bank output by the various output definition approaches. It would be desirable to disaggregate it, but the lack of detailed statistical information rules out this possibility. The second output consists of deposits (y_2), excluding interbank deposits. Ideally, this category should include only transactions deposits, given that our purpose is to proxy the liquidity, payments, and safekeeping services provided. Unfortunately, public information only disentangles savings deposits, other deposits, and interbank deposits. We label this category as "core" deposits, following Kumbhakar *et al.* (2001). Securities and equity investments (y_3), as well as some other earning assets categories (y_4) have also been included in the definition. Finally, we considered some recent contributions which claim the "decline of traditional banking" (Gorton and Rosen, 1995), and others which, following these ideas, suggest that a proxy should be included so as to control for nontraditional activities banks might perform. Hence, our fifth output category (y_5) includes mainly noninterest (commission) income, following (Rogers, 1998). Summary statistics for both inputs and outputs are displayed in Table 2.

5. Results

The prime concern of our study is to analyze the European area as a whole by defining a common frontier for the banks of 14 countries. However, the size of our panel data (571 firms for each one of the seven periods) prevents us from merely displaying estimations and compels us to summarize the results in some coherent manner. Given the nature of our data, the most natural way to synthesize the estimations is to group them into countries in an effort to compare our outcomes to previous works. This process has been accomplished by calculating the country index by the geometric mean of its bank indices. Yet there are some disadvantages attributable to this strategy, since "comparability requires that group-specific mean efficiencies are biased to the same degree, i.e. that the difference is unbiased" (Simar and Steinmann, 2003). The subsample bias depends on both the efficiency density function and the size of each subgroup, and comparisons will be possible only when sub-samples share a common distribution of input-mix. The analysis of whether the distribution of input mix is common or not might be difficult for two subgroups with the same size (Simar and Steinmann, 2003), but it is out of the question in our panel data since each of them is formed from the information on 14 countries, and each subsample includes dissimilar bank sizes (see Table 2). Simar and Zelenyuk (2003) have introduced some heterogeneity in the data,[14] and proposed a test to choose the subsample size by incorporating an arithmetical mean wherein each sub-group is weighted by an economic optimization criterion. Unfortunately their study does not take into account some complications in our paper: the subgroup sizes are fixed as the banks of each country. As far as we know, a procedure to weight the dissimilar size does not exist, unless we group similar countries so as to obtain more comparable subsample sizes. As we have already mentioned, the information about the input-mix distribution of the data is unknown and therefore, an adverse selection of the grouped countries might worsen the bias problem in the sense that the results displayed in the productivity growth analysis (Section 5.1) are geometric means of the indices of each country's banks. However in Section 5.2 we have employed indices based on geometric means of the indices of grouped countries' banks not in order to homogenize the sub-sample size, but to analyze the determinants of productivity change.

5.1. Productivity growth and its decomposition

The analysis of productivity change was carried out through the Malmquist TFP change index—a ratio of efficiency indices estimated over two different time periods. Usually—and this is also the case presented in our study—the time periods considered are consecutive, and the productivity changes for the complete period are not obtained immediately. In order to gauge this kind of summary measure, we worked out two alternative solutions: first of all, we obtained the whole period TFP change index by applying the data of the first and the last time periods ($t_1 = 1995$ and $t_2 = 2001$) in equations of Section 3.2 and, on equal terms, we determined the analogous indices for two other significative subperiods. Secondly and in order to maintain the information of the consecutive years we calculated, for each bank, the geometric mean of all the two consecutive time period indices. Former productivity change estimates are summarized in Table 3. The entries for each country are geometric means of results for individual banks. The last row in each table reports geometric means of results obtained by considering all firms together, i.e., the entire set of EU-14 banking firms in our sample. Results are also split in different ways. First, the sources of productivity change are decomposed following Grosskopf (1993), into their efficiency and technical change components. Second, the sample period is decomposed into two subperiods so as to ease interpretation of results. The economic meaning for this decomposition is relevant for some countries which had joined the EU by 1995, since it could help to disentangle what the effects of EU membership might have been on their respective banking industries. Finally, Table 3 also contains information on significance, enabling us to elucidate whether deviations from unity (productivity growth or decline) are significant or not.[15] In particular, we use single asterisks (*) to indicate those significantly different from unity at the 0.10 level, and double asterisks (**) for entries containing indices significantly different from unity at the 0.05 level.

Since we have followed the input oriented version of the Malmquist TFP change index, entries

[14]The data generating process is defined by considering i.i.d. observations within each subgroup, but not necessary across them.

[15]In order to test significance for the geometric mean of each country we require the empirical distribution of each index, as in Equation (14), but for each country. This is obtained by averaging for each index, the corresponding B bootstrap values of all national banks and afterwards we test for the presence of unity in their percentile confidence interval.

Table 3: Changes in efficiency, technology, and productivity, EU-14 (geometric mean)[a]

	Changes in efficiency (EC)			Changes in technology (TC)			Changes in productivity ($\mathcal{M}$)		
Country	1995/98	1998/01	1995/01	1995/98	1998/01	1995/01	1995/98	1998/01	1995/01
AUSTRIA	0.9945	0.9893**	0.9839**	0.9965*	0.9916**	0.9879**	0.9911**	0.9809**	0.9720**
BELGIUM	0.9778**	1.0243**	1.0015	0.9827**	0.9797**	0.9659**	0.9608**	1.0034	0.9673**
DENMARK	0.9999	1.0209**	1.0208**	0.9969**	0.9936**	0.9867**	0.9969**	1.0144**	1.0072**
FINLAND	1.1128**	0.9002**	1.0017	0.9615**	0.9765**	0.9577**	1.0697**	0.8789**	0.9593**
FRANCE	0.9684**	0.9908	0.9595**	0.9684**	0.9713**	0.9365**	0.9378**	0.9623**	0.8986**
GERMANY	1.0080**	0.9957	1.0037**	0.9781**	0.9886**	0.9651**	0.9859**	0.9844**	0.9686**
IRELAND	0.9807	1.0257*	1.0059	0.9020**	1.0280	0.9240**	0.8846**	1.0544**	0.9295**
ITALY	1.0304**	0.9968	1.0271**	0.9892**	0.9845**	0.9737**	1.0194**	0.9813**	1.0000
LUXEMBOURG	1.0004	0.9960	0.9964	0.9704**	0.9888**	0.9640**	0.9707**	0.9849**	0.9605**
NETHERLANDS	1.0021	1.0228**	1.0251**	1.0014	1.0043	1.0149**	1.0036	1.0273**	1.0404**
PORTUGAL	1.0800**	1.0894**	1.1765**	0.9818**	0.9779**	0.9596**	1.0602**	1.0653**	1.1290**
SPAIN	1.0010	1.0270**	1.0282**	1.0176**	0.9909**	0.9980	1.0187**	1.0176**	1.0262**
SWEDEN	1.0590**	0.9483**	1.0049*	1.0039	0.9710**	1.0080	1.0631**	0.9204**	1.0129**
UNITED KINGDOM	1.0198**	1.0085	1.0285**	0.9917**	0.9663**	0.9597**	1.0113**	0.9746**	0.9871**
Total	1.0001	1.0025**	1.0027**	0.9822**	0.9837**	0.9652**	0.9824**	0.9862**	0.9678**

[a] $EC \times TC = \mathcal{M}$.

(*), (**): significant differences from unity at 10% and 5%, respectively. A number > 1 indicates decline; a number < 1 indicates growth.

below unity indicate **productivity growth**, whereas those greater than one indicate **productivity decline**.[16] Residually, entries equal to one indicate **stagnation**. In addition, the sensitivity analysis performed in this study adds extra insights to the interpretation of results, since in a number of instances productivity growth, or decline, is not found to be significant.

Other results in Table 3 relate to the decomposition of productivity; as stated above, productivity growth/decline can be decomposed into movements of banks within the input/ output space (changes in efficiency) and into movement of the boundary of the production set over time (changes in technology). In both circumstances, entries are interpreted similarly. In the case of efficiency, indices below unity indicate **efficiency gains**, indices above unity indicate **efficiency losses**, whereas an index equal to unity would indicate stagnation. Like productivity, entries without asterisks indicate that changes are not significant, which occurs in a number of cases. Finally, technical change must also be interpreted analogously to efficiency change: values greater than one indicate **technical regress**, values below one indicate **technical progress**, and values equal to one indicate no technical change. Note that, as stated by Grosskopf (1993), productivity growth may simultaneously involve technical regress and efficiency gains, or technical progress and efficiency losses.[17]

Table 3 shows that, overall, the latter has prevailed. As revealed by the last row in the Table, productivity growth has occurred for the overall period 1995–2001, with no remarkable differences between the two subperiods 1995–1998 and 1998–2001, considering all firms and countries together. As of 2001, European banks were providing, on average, 103.3% (resulting from inverting 0.9678) as much output per unit of input as in 1995, which is an accumulated growth of 3.3%. This productivity growth has simultaneously involved technical progress (3.61%) and efficiency losses (−0.27%). However, results reveal that productivity growth has not prevailed for all EU countries. In particular, Portugal, Spain, The Netherlands, Denmark and Sweden have gone through significant productivity decline. More specifically, the cases of The Netherlands and Sweden simultaneously combine significant technical regress with efficiency decrease, while in the other cases, productivity decline has resulted from a significant decrease of efficiency with significant technical progress. Italian banks' productivity has remained constant during the whole period. On the other hand, productivity has significantly improved in Austria, Belgium, Finland, France, Germany, Ireland, Luxembourg and the UK.

Tables 4, 5 and 6 show, respectively, efficiency change, technical change, and productivity change for pairs of consecutive years. The last column in each table contains annual changes for each variable—computed as geometric means of the annual geometric means.[18] The annual figures suggest that productivity has been growing at a modest rate (+0.57% per year, as revealed by Table 6). Again, productivity growth seems to have been brought about by technological change, which has been growing modestly (+0.62% per year); on the other hand, efficiency has declined very slightly (−0.04% per year), yet not enough to become significant.

[16] If we had followed the output oriented version of the Malmquist TFP change index, interpretation of results would reverse. This is possible due to the constant returns to scale (CRS) assumption.

[17] Similar possibilities exist for the case of productivity decline.

[18] Following Simar and Wilson (1998a), when averaging bank estimates over time, we also average the corresponding bootstrap values over the time to obtain estimates of significance for the complete period.

Table 4: Changes in efficiency (EC), consecutive years, EU-14 (geometric mean)[a]

Country	1995/96	1996/97	1997/98	1998/99	1999/00	2000/01	1995/01
AUSTRIA	1.0037**	0.9972	0.9936**	0.9966**	0.9948**	0.9980	0.9973**
BELGIUM	0.9896**	0.9941*	0.9939**	1.0065**	1.0143**	1.0033	1.0003
DENMARK	0.9979**	0.9989	1.0031*	1.0001	1.0141**	1.0066**	1.0034**
FINLAND	0.9917	1.0480**	1.0706**	0.9737**	0.9532**	0.9700**	1.0003
FRANCE	0.9853**	0.9762**	1.0068	0.9896**	1.0054	0.9959	0.9931**
GERMANY	1.0011	0.9958	1.0111**	0.9983	0.9988	0.9987	1.0006**
IRELAND	0.9983	0.9968	0.9856**	1.0084	1.0138	1.0033	1.0010
ITALY	1.0394**	0.9935**	0.9979	0.9905**	0.9972*	1.0091**	1.0045**
LUXEMBOURG	1.0002	1.0001	1.0001**	0.9896**	1.0036*	1.0028	0.9994**
NETHERLANDS	1.0068**	1.0039	0.9915**	1.0204**	1.0104**	0.9920**	1.0041**
PORTUGAL	1.0198**	0.9929**	1.0666**	1.0281**	1.0090**	1.0501**	1.0275**
SPAIN	0.9978**	1.0051**	0.9983	1.0133**	1.0044**	1.0092*	1.0046**
SWEDEN	1.0146**	0.9919	1.0529**	1.0164**	1.0608**	0.8795**	1.0008
UNITED KINGDOM	1.0061**	1.0098**	1.0038	0.9917**	1.0212**	0.9959*	1.0047**
Total	1.0009	0.9942**	1.0050**	0.9971	1.0053**	1.0001	1.0004

[a] $EC \times TC = \mathcal{M}$.
(*), (**): significant differences from unity at 10% and 5%, respectively. A number >1 indicates decline; a number <1 indicates growth.

Table 5: Changes in technology (TC), consecutive years, EU-14 (geometric mean)[a]

Country	1995/96	1996/97	1997/98	1998/99	1999/00	2000/01	1995/01
AUSTRIA	0.9998	1.0012	0.9972	0.9981	0.9802**	0.9991	0.9959**
BELGIUM	0.9991	1.0011	0.9383**	0.9906**	0.9897*	0.9958	0.9855**
DENMARK	0.9959**	1.0002	1.0004	0.9968**	0.9932**	1.0036**	0.9983**
FINLAND	0.9930	1.0041	0.9595**	0.9954	0.9606**	0.9953	0.9845**
FRANCE	0.9725**	1.0068*	0.9874	0.9996	0.9386**	1.0219**	0.9874**
GERMANY	0.9903**	0.9913**	0.9998**	1.0106**	0.9887**	0.9859**	0.9944**
IRELAND	0.9912	0.9451**	0.9598**	0.9815**	1.0740**	1.0104	0.9928*
ITALY	0.9988	0.9972**	0.9912**	0.9919**	0.9894**	1.0074**	0.9960**
LUXEMBOURG	0.9869**	0.9832**	1.0009**	1.0018	0.9920**	0.9846**	0.9915**
NETHERLANDS	1.0046	1.0027	0.9996	1.0004	0.9983	1.0073**	1.0022
PORTUGAL	0.9952*	1.0019	0.9872**	1.0016	0.9913**	1.0000	0.9962**
SPAIN	1.0211**	0.9984	1.0297**	0.9972*	0.9999	0.9903**	1.0060**
SWEDEN	1.0239	1.0054	0.9705**	0.9659**	0.9262**	1.0673**	0.9922**
UNITED KINGDOM	0.9978	1.0074*	0.9920**	0.9918*	0.9783**	0.9990	0.9944**
Total	0.9915**	0.9976**	0.9949	0.9996	0.9786**	1.0009	0.9938**

[a] $EC \times TC = \mathcal{M}$.
(*), (**): significant differences from unity at 10% and 5%, respectively. A number >1 indicates decline; a number <1 indicates growth.

Table 6: Changes in productivity ($\mathcal{M}$), consecutive years, EU-14 (geometric mean)[a]

Country	1995/96	1996/97	1997/98	1998/99	1999/00	2000/01	1995/01
AUSTRIA	1.0035**	0.9984**	0.9909**	0.9946**	0.9750**	0.9971	0.9932**
BELGIUM	0.9887**	0.9952**	0.9326**	0.9971**	1.0038	0.9991	0.9858**
DENMARK	0.9938**	0.9990	1.0035**	0.9969**	1.0072**	1.0102**	1.0018**
FINLAND	0.9847**	1.0523**	1.0273**	0.9692**	0.9156**	0.9655**	0.9848**
FRANCE	0.9582**	0.9828**	0.9941**	0.9892**	0.9436**	1.0178**	0.9807**
GERMANY	0.9914**	0.9872**	1.0108**	1.0088**	0.9875**	0.9846**	0.9950**
IRELAND	0.9895	0.9421**	0.9460**	0.9898**	1.0889**	1.0137	0.9938**
ITALY	1.0382**	0.9907**	0.9891**	0.9825**	0.9867**	1.0165**	1.0004
LUXEMBOURG	0.9870**	0.9833**	1.0010	0.9914**	0.9955	0.9874**	0.9909**
NETHERLANDS	1.0115**	1.0067**	0.9911**	1.0208**	1.0087**	0.9993	1.0063**
PORTUGAL	1.0149**	0.9948**	1.0530**	1.0297**	1.0002	1.0501**	1.0236**
SPAIN	1.0188**	1.0034**	1.0280**	1.0104**	1.0043**	0.9994	1.0107**
SWEDEN	1.0389**	0.9972	1.0219**	0.9818**	0.9825**	0.9387**	0.9930**
UNITED KINGDOM	1.0039**	1.0172**	0.9958**	0.9836**	0.9990	0.9949**	0.9990**
Total	0.9924**	0.9918**	0.9999**	0.9968**	0.9838**	1.0011*	0.9943**

[a] $EC \times TC = \mathcal{M}$.
(*), (**): significant differences from unity at 10% and 5%, respectively. A number >1 indicates decline; a number <1 indicates growth.

Following the motivation presented in Section 1, it must be noticed that results are not significant in a number of instances. The bootstrap analysis provides us with a large amount of meaningful information both at country and, especially, at *firm* level. In particular, application of the bootstrap allows assessment of the "null hypothesis" of no efficiency change, no technical change, and no productivity growth/decline, indicating that the corresponding measures are not statistically different from unity. We provide results for 90% and 95% confidence intervals, whose interpretation is straightforward: in the 95% case, if it contains the unity, then the corresponding measure is not significantly different from one at the 5% significance level, i.e., we cannot elucidate whether changes occurred in efficiency, technology, or productivity. Alternatively, when the interval excludes unity, we can elucidate that the corresponding index is significantly different from unity. A summary of results on significance is reported in Table 7, for all EU-14 countries. Appendix A provides summaries for each particular country. Results for the whole sample suggest that out of 279 firms going through productivity growth over the 1995–2001 period, 258 were found to be significant. On the other hand, out of the 222 firms going through productivity decline, only in 20 instances was it not significant—and in two cases it was significant at the 10% significance level.

Table 7: Summary of bootstrap results for changes in efficiency, technology, and productivity, EU-14

	1995/98			1998/01			1995/01		
Changes in efficiency									
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	227	193	4	205	166	3	220	188	4
Decline	191	157	6	228	200	9	236	213	4
Stagnation	153			138			115		
Changes in technology									
	1995/98			1998/01			1995/01		
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	150	86	10	135	85	11	197	158	10
Decline	49	6	2	29	7	4	22	5	2
Stagnation	372			407			352		
Changes in productivity									
	1995/98			1998/01			1995/01		
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	279	262	1	253	232	2	279	258	0
Decline	196	177	4	220	194	5	222	200	2
Stagnation	96			98			70		

Considering technical change, we find that overall productivity growth experience at EU level during 1995–2001 occurred in only 168 firms, i.e., those for which technical progress was found to be significant either at 5% (158 firms) or at 10% (10 firms) level; for the remaining 29 firms—giving a total of 197—technical progress was not significant. Significant technical regress was found only for 5 and 2 firms at 5% and 10% significance level, respectively. Residually, we find that 352 firms did not go through either technical progress or regress. On the other hand, efficiency change appears to be the primary driver of productivity decline, since 217 firms experienced significant efficiency losses for the period 1995–2001; in 19 instances, however, efficiency losses were not found to be significant. These results show lower changes in all the indices than the corresponding values in Table 3 and it proves the appreciable change in the composition of the data when comparing the first and the last time periods, an effect that is softened, however, when looking at the changes that occurred every two consecutive years during the complete period.

Our results are not exactly coincidental with those obtained by previous studies that analyze productivity growth for European banks. In their study, Casu *et al.* (2004) find Spain and Italy to be the countries going through faster productivity growth. In our case, the only countries trailing behind Spain are Portugal and The Netherlands; Italy also trails behind Austria, Belgium, Finland, Germany, Ireland, Luxembourg and the UK (see last column in Table 3). On the other hand, in their study French banks do not perform too brilliantly, at least compared with banks from other countries; in contrast, our results point out that these are the banks which are experiencing faster productivity growth.

These results, far from being disappointing, help to triangulate those of Casu *et al.* (2004), the results obtained by Dietsch and Lozano-Vivas (2000), Chaffai *et al.* (2001), and ours. Note that, in the first case, estimations are carried out on individual countries, whereas we consider a common frontier; in addition, our sample is made up of a larger number of countries. The studies by Dietsch and Lozano-Vivas (2000) and Chaffai *et al.* (2001), which compare the efficiency of several European banking industries finding that, when controlling for country-specific environmental variables, results do not differ dramatically.

5.2. On the determinants of productivity change

Our study analyzes all firms together, regardless of their home country—i.e., we specify a common frontier. In other words, estimations are not carried out on individual countries, but rather on a European Union basis. Notwithstanding, there is some evidence (Chaffai *et al.*, 2001; Dietsch and Lozano-Vivas, 2000) to suggest that environmental variables are still relevant, even with the liberalization turmoil in Europe. On the other hand, some recent changes in the European banking industry suggest some banks are run at European scale.[19] In addition, the study by Dietsch and Lozano-Vivas (2000), confined entirely to efficiency analysis, considers the 1988–1992 period, in which some important changes were still taking place in many countries. On the other hand, Chaffai *et al.* (2001) focus on productivity, and consider a more up-to-date database (1992–1997), achieving similar results to those in Dietsch and Lozano-Vivas (2000).

Therefore, despite suggestions in the previous literature suggesting that environmental variables matter, we adopt a different strategy consisting of entering the country-specific variables—or whatever other variables one might consider that may affect banks' performance—in a second stage of the analysis. Although the factors that might determine what drives the performance of financial institutions are multiple (see Harker and Zenios, 2000), our study will focus on those related to the relevance of environmental variables and enhanced financial integration.

In fact, in this section we merge two stems of research. On the one hand, we consider studies such as those commented on above which control for environmental variables when comparing the efficiency—or productivity—of different banking systems. On the other hand, our aims are also coincidental with those followed by the so-called two-stage models that attempt to ascertain the (likely) determinants of efficiency and/or productivity. Most of these two-stage studies have notable disadvantages, put

[19] Such as the recent takeover of Abbey National by Santander Central Hispano, Spain's largest bank.

forward by Simar and Wilson (2003) and Daraio and Simar (2005a,b). Specifically, after measuring either efficiency or productivity in a first stage using nonparametric techniques, most of them consider parametric techniques (basically OLS and censored regression models) to disentangle what determines the results obtained in the first stage. This constitutes not only an inconsistency in itself; in addition, there are problems related to the fact that DEA efficiency/productivity estimates are dependent in the statistical sense (they are computed using linear programming techniques) and, consequently, standard approaches to inference are invalid (Simar and Wilson, 2003). So as to overcome these problems, these authors suggest employing bootstrap methods which fully describe the Data Generating Process (DGP).

Alternatively, we suggest a different, simpler methodology which enters country-specific effects (or environmental variables) in the second stage of the analysis in a different way. In our case, consistency is achieved since the suggested technique shares the nonparametric flavor present in the first stage of the analysis. The specifics of the conditioning scheme presented here operate through several steps. First, modified series of productivity indices are requested, which are calculated on the different hypotheses considered. In particular, our hypotheses are related to financial integration factors, and we will ask specifically here if nation-state factors (environmental variables), physical-neighborhood spillover effects, or the enhanced financial integration over time after joining the EU help explain the observed discrepancies amongst European banks. Thus, this section asks questions such as how integrated European banking systems have become (or if they still resemble isolated islands), how much does knowing the host country's banking productivity explain that of the bank, or the surrounding countries', or even how much it is explained by knowing the banking productivity of the countries which joined the EU at the same time (Quah, 1995).

Therefore, normalization is performed in order to construct new indicators of productivity indices, namely, $\widehat{\mathcal{M}}_j^{EU}$, $\widehat{\mathcal{M}}_j^{c}$, $\widehat{\mathcal{M}}_j^{n}$, $\widehat{\mathcal{M}}_j^{m}$, which should be interpreted as the productivity indices for firm j divided by the relevant average. For instance, in the first case ($\widehat{\mathcal{M}}_j^{EU}$) we are dividing each bank's productivity by the European average; this is equivalent to conditioning on European information, the same way as in the $\widehat{\mathcal{M}}_j^{c}$ we would be conditioning on host nation-state information. Once these series have been calculated, we estimate, using nonparametric methods, the densities corresponding to each variable for each period under analysis. Details on this have been deferred to Appendix B. Then, if probability mass of, say, $\widehat{\mathcal{M}}^{c}$ were more tightly concentrated around unity than that corresponding to, say, $\widehat{\mathcal{M}}^{EU}$, it would suggest that, in terms of productivity, when compared to their home country peers, European banks are more alike than when compared to the rest of the European banks. Hence, a country effect would exist or, put differently, environmental variables matter. However, the scenarios might be multiple, since densities exhibiting multi-modality would suggest some groups of banks perform much better (or much worse) than others, and if that country-effect smoothed away the obtained multi-modality, it could indicate that there are no clusters of banks with differing performances, but rather some omitted, environmental, variables. Under this hypothesis we would be assuming that the liberalization undergone by European banking systems was the primary force driving productivity growth in European banking. If that were the case, i.e., if each bank's productivity index was similar to that of other banks in other countries, densities should be concentrated around the unity—since we divided by the EU-14 geometric mean. If the trend were to continue, probability mass should concentrate more tightly over time—i.e., for the period 1998–2001.

We also consider that European banking systems are not like isolated islands. Accordingly, each bank's performance could be predicted by both that in surrounding countries and in the host state (Quah, 1995). In this case, we compare the densities of variable $\widehat{\mathcal{M}}^n$ with those obtained for the remainder—$\widehat{\mathcal{M}}^{EU}$, $\widehat{\mathcal{M}}^c$, and $\widehat{\mathcal{M}}^m$. The $\widehat{\mathcal{M}}^n$ variable is constructed by dividing the productivity index obtained for each bank by the average of those banks in its home country <u>and</u> its economic neighborhood countries.[20] The interpretations would be analogous to those considered above. Therefore, if densities corresponding to $\widehat{\mathcal{M}}^n$ are tighter than, for instance, those corresponding to $\widehat{\mathcal{M}}^{EU}$, it would indicate that banks' productivity in physically-close banking systems are closer than when all European countries are taken together, although the likely scenarios here could also be multiple.

Finally, we consider that the differing dates at which countries joined the European Union might have also played a relevant role. The $\widehat{\mathcal{M}}^m$ variable would reflect this. It is constructed by dividing each bank's productivity index by the average corresponding to the banks in countries which joined the EU simultaneously.[21] Therefore, if densities corresponding to $\widehat{\mathcal{M}}^m$ were tighter than those corresponding to, say, $\widehat{\mathcal{M}}^{EU}$, it would indicate that banks in countries which joined the EU at the same time perform more similarly than when compared to their peers in other EU countries—although, once more, the scenarios could vary a great deal.

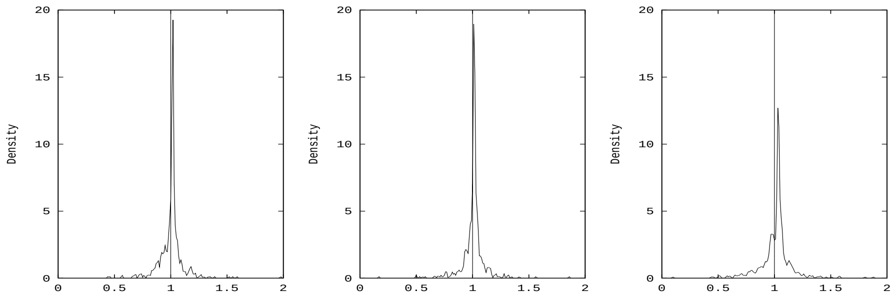
Results are shown in Figure 1.[22] The results are not exactly coincidental with those finding that country-specific effects exist. Densities are especially tighter and more concentrated when dividing by the European average (Figure 1.a). As shown by Figure 1.a, the results are coincidental for each subperiod considered. In contrast, dividing by each country averages (Figure 1.b) yields densities whose probability mass is more spread. However, these results have some nuances and must be interpreted with care. For instance, Figure 1.a, regardless of the period considered, exhibits both probability mass tightly concentrated around unity but, simultaneously, a remarkable amount of multi-modality, as shown by several tiny bumps. Therefore, although there are many European banks with similar performance, driving densities to concentrate tightly around unity, many differences still prevail after dividing by the average.

[20]We consider six economic neighborhoods, namely: i) The Netherlands, Belgium, and Luxembourg; ii) Sweden, Finland, and Denmark; iii) United Kingdom and Ireland; iv) Austria and Germany; v) France and Italy; and vi) Portugal and Spain. Whereas in most cases they are clearly a reality, in some others they are not so apparent.

[21]We consider three groups: i) The Netherlands, Belgium, Luxembourg, Italy, France, Germany, United Kingdom, Ireland, and Denmark; ii) Portugal and Spain; and iii) Sweden, Finland, and Austria. Although the first group contains countries which joined the EU at different points in time, we consider that sufficient time has passed to assume their financial systems are not going to become much more integrated—at least in the short run.

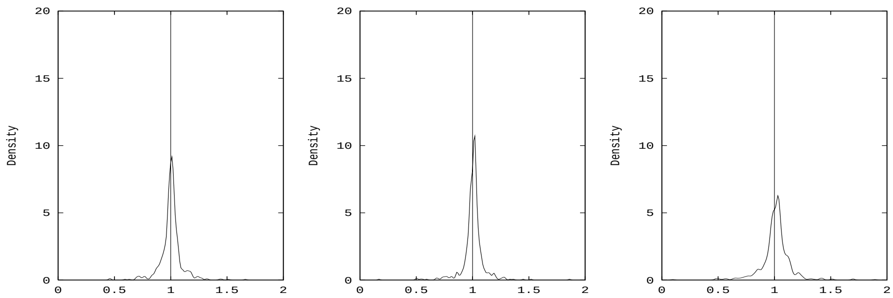
[22]We have confined the analysis to the analysis of Malmquist productivity indices, omitting their decomposition into efficiency and technical change, so as to save space. Results are available upon request.

Figure 1: Productivity growth in European banking, densities



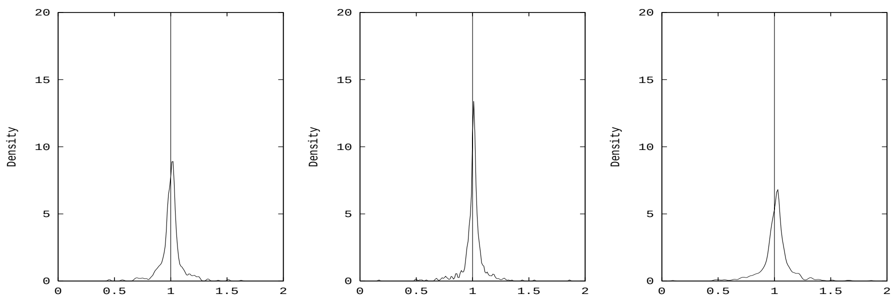
1995–1998 **1998–2001** **1995–2001**

(a) EU14-conditioned



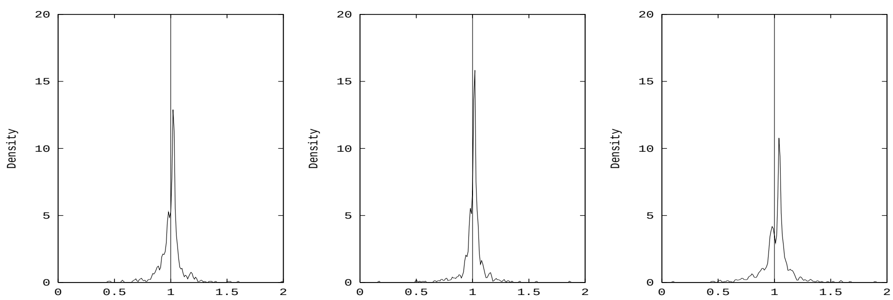
1995–1998 **1998–2001** **1995–2001**

(b) Country-conditioned



1995–1998 **1998–2001** **1995–2001**

(c) Economic neighbor-conditioned



1995–1998 **1998–2001** **1995–2001**

(d) Time of membership-conditioned

The European integration effect also overwhelms that relating to the physical-neighborhood (Figure 1.c) as well as that related to the speed of financial integration (Figure 1.d). Conditioning by the economic-neighbors average yields results which do not differ a great deal from those found when conditioning by each country average. Considering the time when each country joined the EU provides us with better results in terms of tighter densities, yet not as much as those found when conditioning for the European average.

Ideally, one should also be able to test whether differences in densities are statistically significant. Since the analysis considered above is based on comparing the results yielded by different linear programming problems which fall under the broad category of nonparametric techniques to measure productivity, we can also exploit recent developments in nonparametric methods to test formally whether densities differ. Specifically, following Fan and Ullah (1999), we may test whether two unknown distributions, which in our specific setting would be related to those for the different variables considered ($\widehat{\mathcal{M}}^{EU}$, $\widehat{\mathcal{M}}^{c}$, $\widehat{\mathcal{M}}^{n}$, $\widehat{\mathcal{M}}^{m}$), differ significantly. Therefore, if f and g are the distributions corresponding to, say, $\widehat{\mathcal{M}}^{EU}$ and $\widehat{\mathcal{M}}^{c}$ for the 1995–1998 subperiod, the null hypothesis being tested would be $H_0 : f(\widehat{\mathcal{M}}^{EU}) = g(\widehat{\mathcal{M}}^{c})$ against the alternative, $H_1 : f(\widehat{\mathcal{M}}^{EU}) \neq g(\widehat{\mathcal{M}}^{c})$. The specifics of the test have been deferred to Appendix B.

Table 8 provides us with the results of the test at the 1% significance level. Although there are more testable hypotheses, we have restricted the analysis to the most relevant ones. As we might *a priori* expect, the only case in which the hypothesis of equality between two distributions cannot be rejected is $H_0 : f(\widehat{\mathcal{M}}^{c}) = g(\widehat{\mathcal{M}}^{n})$. For all other cases, the hypothesis is rejected at the 1% significance level.

6. Conclusions

This article has analyzed productivity growth in European banking over the 1995–2001 post-deregulation period. This is an interesting field of research in which contributions to date have been minimal. Although the empirical evidence regarding the efficiency of specific European banking systems is quite remarkable, there are few studies that jointly consider different European countries. Our study introduces a small novelty by encompassing virtually all European Union banking systems—all except Greece and the countries that joined the EU in 2004, since they were not members as of 2001, the last period of our study. In addition, we also focus on productivity, an area in which contributions on international comparisons, once more, are almost entirely yet to come when taking European banking industries simultaneously. It is of special interest since, as suggested by Färe *et al.* (1994b), it is possible to decompose productivity into its technical change and efficiency change components.

However, the tools provided by Färe *et al.* (1994b) do not provide means to conduct statistical inference, given their deterministic nature. Yet Simar and Wilson (1998c, 1999, 2000b) have defined a statistical model which allows for the determination of the statistical properties of the nonparametric productivity estimators in the multi-input and multi-output case. The important practical implication of their findings is that statistical inference is possible. Their model is based on the *bootstrap*, a computer-intensive technique based on the basic idea of approximating the unknown statistic's

Table 8: Distribution hypothesis tests using Li (1996) test

Variable	Null hypothesis (H_0)	1995/98		1998/01		1995/01	
		T-test statistics	One-percent significance level (critical value: 2.33)	T-test statistics	One-percent significance level (critical value: 2.33)	T-test statistics	One-percent significance level (critical value: 2.33)
Productivity change	$f(\widehat{\mathcal{M}}^{EU}) = g(\widehat{\mathcal{M}}^{c})$	25.618	H_0 rejected	13.260	H_0 rejected	11.399	H_0 rejected
	$f(\widehat{\mathcal{M}}^{EU}) = g(\widehat{\mathcal{M}}^{n})$	22.028	H_0 rejected	12.176	H_0 rejected	13.087	H_0 rejected
	$f(\widehat{\mathcal{M}}^{EU}) = g(\widehat{\mathcal{M}}^{m})$	23.087	H_0 rejected	5.947	H_0 rejected	20.645	H_0 rejected
	$f(\widehat{\mathcal{M}}^{c}) = g(\widehat{\mathcal{M}}^{n})$	0.960	H_0 not rejected	6.395	H_0 rejected	0.720	H_0 not rejected

sampling distribution of interest by resampling from an original sample extensively, and then using this simulated sampling distribution to make population inferences.

The usage of bootstrapping techniques turns out to be quite relevant in our study because of the characteristics of the data employed. Although the sample considered contains the most important commercial banks in each banking industry, unavailable data for some firms could jeopardize the reliability of our results. The issue is addressed by considering the bootstrap, whose resampling features are particularly relevant when the whole sample is not available. However, neither of the only two studies that analyze productivity growth at the international level used bootstrapping techniques to solve the problem of statistical significance; thus, the present study is the first to analyze the banking productivity of a large set of countries using resampling techniques.

Results show that significant productivity growth (3.3%) has occurred for the overall 1995–2001 period, with no remarkable differences between the two subperiods into which the sample was split (1995–1998 and 1998-2001). This productivity growth has simultaneously involved technical progress and efficiency losses. The improvement in "best practice" (technical progress) has occurred both in 1995–1998 and 1998–2001, resulting in +3.61% technical progress for the overall period 1995-2001. In contrast, efficiency worsened by −0.27%.

However, this significant productivity growth has not been a common feature for all EU countries. In particular, Portugal, Spain, Netherlands, Denmark and Sweden have experienced significant productivity decline. More specifically, except for The Netherlands and Sweden, which combine technical regress and efficiency decline, in all other instances productivity decline has resulted from a significant worsening in efficiency accompanied by technical progress. We only found stagnation in the Italian case. On the other hand, productivity has increased significantly in Austria, Belgium, Finland, France, Germany, Ireland, Luxembourg and the United Kingdom.

These results are not exactly coincidental with those obtained by previous studies analyzing productivity growth in European banks (Casu *et al.* (2004), Dietsch and Lozano-Vivas (2000) and Chaffai *et al.* (2001)). The difference could be due to the different methodologies (common frontier vs individual frontier) and/or the consideration of larger sample of countries considered in the present study.

In an attempt to ascertain what the determinants of productivity differentials among firms might be, we performed a second-stage analysis. In contrast to most of these studies, in which nonparametric techniques are used to measure efficiency or productivity, but parametric techniques are considered to find out their determinants (the notable flaws of which have been put forward by Simar and Wilson (2003)), we consider a fully nonparametric approach. The set of variables chosen is basically related to financial integration issues, although it would be straightforward to consider different sets of control variables. Results show that the importance of operating in a common country-specific environment could be lessened when analyzing productivity, and that there are most firms whose productivity levels are quite similar in spite of their different nationalities.

A. Country specific summary of bootstrap results

This appendix presents summaries of bootstrap results for each particular country in our sample. It contains results on significance for each particular firm in each country, presented in Tables 9 to 22.

Table 9: Summary of bootstrap results for changes in efficiency, technology, and productivity, Austria

	1995/98			1998/01			1995/01		
Changes in efficiency									
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	8	7	0	13	13	0	10	10	0
Decline	7	7	0	5	4	1	8	8	0
Stagnation	5			2			2		
Changes in technology									
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	3	1	0	2	1	1	4	3	0
Decline	1	0	0	0	0	0	0	0	0
Stagnation	16			18			16		
Changes in productivity									
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	8	8	0	14	13	0	11	10	0
Decline	7	7	0	4	3	0	7	6	0
Stagnation	5			2			2		

Table 10: Summary of bootstrap results for changes in efficiency, technology, and productivity, Belgium

	1995/98			1998/01			1995/01		
Changes in efficiency									
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	9	7	0	3	3	0	4	3	0
Decline	3	2	0	11	10	0	10	10	0
Stagnation	6			4			4		
Changes in technology									
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	3	1	1	4	2	1	4	4	0
Decline	1	0	0	0	0	0	1	0	0
Stagnation	14			14			13		
Changes in productivity									
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	11	10	0	6	5	0	6	5	0
Decline	3	3	0	10	10	0	10	10	0
Stagnation	4			2			2		

Table 11: Summary of bootstrap results for changes in efficiency, technology, and productivity, Denmark

	1995/98			1998/01			1995/01		
Changes in efficiency									
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	18	16	0	10	9	0	12	10	0
Decline	6	7	0	16	15	0	15	14	0
Stagnation	17			15			14		
Changes in technology									
	1995/98			1998/01			1995/01		
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	2	2	1	2	3	0	4	5	0
Decline	0	0	0	0	0	0	0	0	0
Stagnation	39			39			37		
Changes in productivity									
	1995/98			1998/01			1995/01		
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	18	17	0	11	10	0	13	13	0
Decline	6	6	0	15	15	0	14	14	0
Stagnation	17			15			14		

Table 12: Summary of bootstrap results for changes in efficiency, technology, and productivity, Finland

	1995/98			1998/01			1995/01		
Changes in efficiency									
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	0	0	0	2	1	0	1	1	0
Decline	3	2	0	1	1	1	2	2	0
Stagnation	0			0			0		
Changes in technology									
	1995/98			1998/01			1995/01		
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	2	0	0	2	1	0	2	2	0
Decline	0	0	0	0	0	0	0	0	0
Stagnation	1			1			1		
Changes in productivity									
	1995/98			1998/01			1995/01		
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	1	0	0	2	2	0	2	2	0
Decline	2	3	0	1	1	0	1	1	0
Stagnation	0			0			0		

Table 13: Summary of bootstrap results for changes in efficiency, technology, and productivity, France

	1995/98			1998/01			1995/01		
Changes in efficiency									
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	80	73	0	52	47	1	73	66	1
Decline	29	26	0	56	51	2	40	37	0
Stagnation	17			18			13		
Changes in technology									
	1995/98			1998/01			1995/01		
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	41	27	1	34	28	3	48	42	1
Decline	10	2	0	8	3	2	5	1	1
Stagnation	75			84			73		
Changes in productivity									
	1995/98			1998/01			1995/01		
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	91	89	0	69	67	0	92	88	0
Decline	29	23	2	45	40	1	29	30	0
Stagnation	6			12			5		

Table 14: Summary of bootstrap results for changes in efficiency, technology, and productivity, Germany

	1995/98			1998/01			1995/01		
Changes in efficiency									
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	37	30	1	49	38	1	41	37	1
Decline	37	26	4	34	27	1	42	34	2
Stagnation	44			35			35		
Changes in technology									
	1995/98			1998/01			1995/01		
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	25	10	1	22	12	2	33	21	5
Decline	14	1	0	8	2	2	7	0	0
Stagnation	79			88			78		
Changes in productivity									
	1995/98			1998/01			1995/01		
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	50	46	1	55	47	1	53	48	0
Decline	43	42	0	37	30	1	43	35	1
Stagnation	25			26			22		

Table 15: Summary of bootstrap results for changes in efficiency, technology, and productivity, Ireland

Changes in efficiency									
	1995/98			1998/01			1995/01		
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	3	2	0	0	0	0	1	1	0
Decline	1	2	0	4	3	0	3	3	0
Stagnation	3			3			3		
Changes in technology									
	1995/98			1998/01			1995/01		
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	2	2	0	1	0	0	4	3	1
Decline	1	0	0	2	1	0	0	0	0
Stagnation	4			4			3		
Changes in productivity									
	1995/98			1998/01			1995/01		
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	5	4	0	1	0	0	4	3	0
Decline	2	2	0	6	4	0	3	3	0
Stagnation	0			0			0		

Table 16: Summary of bootstrap results for changes in efficiency, technology, and productivity, Italy

Changes in efficiency									
	1995/98			1998/01			1995/01		
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	17	17	0	26	24	0	20	19	0
Decline	31	27	0	22	18	1	28	24	0
Stagnation	1			1			1		
Changes in technology									
	1995/98			1998/01			1995/01		
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	26	18	3	18	7	2	34	32	1
Decline	2	0	0	1	0	0	0	0	0
Stagnation	21			30			15		
Changes in productivity									
	1995/98			1998/01			1995/01		
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	20	21	0	30	30	0	23	24	0
Decline	28	25	1	18	15	1	25	22	0
Stagnation	1			1			1		

Table 17: Summary of bootstrap results for changes in efficiency, technology, and productivity, Luxembourg

Changes in efficiency									
	1995/98			1998/01			1995/01		
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	27	16	3	17	7	1	25	15	1
Decline	17	9	1	20	16	2	21	18	1
Stagnation	21			28			19		
Changes in technology									
	1995/98			1998/01			1995/01		
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	25	11	2	24	14	0	33	22	2
Decline	7	0	1	6	1	0	3	1	0
Stagnation	33			35			29		
Changes in productivity									
	1995/98			1998/01			1995/01		
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	36	32	0	27	21	1	36	29	0
Decline	18	11	0	24	19	1	21	16	1
Stagnation	11			14			8		

Table 18: Summary of bootstrap results for changes in efficiency, technology, and productivity, Netherlands

Changes in efficiency									
	1995/98			1998/01			1995/01		
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	6	6	0	4	2	0	6	3	1
Decline	11	8	1	13	13	0	12	12	0
Stagnation	4			4			3		
Changes in technology									
	1995/98			1998/01			1995/01		
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	2	1	0	6	1	1	4	0	0
Decline	5	1	1	1	0	0	2	1	1
Stagnation	14			14			15		
Changes in productivity									
	1995/98			1998/01			1995/01		
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	7	7	0	4	4	0	5	4	0
Decline	12	11	1	14	14	0	14	13	0
Stagnation	2			3			2		

Table 19: Summary of bootstrap results for changes in efficiency, technology, and productivity, Portugal

Changes in efficiency									
	1995/98			1998/01			1995/01		
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	0	1	0	2	2	0	0	0	0
Decline	10	9	0	8	8	0	10	10	0
Stagnation	0			0			0		
Changes in technology									
	1995/98			1998/01			1995/01		
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	1	1	0	2	2	0	4	4	0
Decline	0	0	0	0	0	0	0	0	0
Stagnation	9			8			6		
Changes in productivity									
	1995/98			1998/01			1995/01		
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	1	2	0	2	2	0	0	0	0
Decline	9	8	0	8	8	0	10	9	0
Stagnation	0			0			0		

Table 20: Summary of bootstrap results for changes in efficiency, technology, and productivity, Spain

Changes in efficiency									
	1995/98			1998/01			1995/01		
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	8	6	0	2	3	0	6	5	0
Decline	12	12	0	25	23	1	26	24	1
Stagnation	24			17			12		
Changes in technology									
	1995/98			1998/01			1995/01		
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	3	2	0	3	4	0	3	3	0
Decline	1	1	0	1	0	0	1	1	0
Stagnation	40			40			40		
Changes in productivity									
	1995/98			1998/01			1995/01		
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	11	8	0	4	5	0	8	8	0
Decline	13	12	0	26	24	1	27	24	0
Stagnation	20			14	24		9		

Table 21: Summary of bootstrap results for changes in efficiency, technology, and productivity, Sweden

	1995/98			1998/01			1995/01		
CHANGES IN EFFICIENCY									
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	2	0	0	5	2	0	3	1	0
Decline	3	2	0	0	0	0	2	2	0
Stagnation	0			0			0		
CHANGES IN TECHNOLOGY									
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	3	3	0	4	2	0	3	3	0
Decline	2	1	0	0	0	0	1	1	0
Stagnation	0			1			1		
CHANGES IN PRODUCTIVITY									
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	3	2	0	5	4	0	4	2	0
Decline	2	3	0	0	0	0	1	2	0
Stagnation	0			0			0		

Table 22: Summary of bootstrap results for changes in efficiency, technology, and productivity, United Kingdom

	1995/98			1998/01			1995/01		
CHANGES IN EFFICIENCY									
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	12	12	0	20	15	0	18	17	0
Decline	21	18	0	13	11	0	17	15	0
Stagnation	11			11			9		
CHANGES IN TECHNOLOGY									
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	12	7	1	11	8	1	17	14	0
Decline	5	0	0	2	0	0	2	0	0
Stagnation	27			31			25		
CHANGES IN PRODUCTIVITY									
	Original	5%	10%	Original	5%	10%	Original	5%	10%
Growth	17	16	0	23	22	0	22	22	0
Decline	22	21	0	12	11	0	17	15	0
Stagnation	5			9			5		

B. Nonparametric estimation of density functions and tests for the closeness between distributions

B.1. Nonparametric density estimation of productivity indices

We performed the nonparametric estimation of densities using kernel smoothing. The kernel density estimate $\hat{f}$ of a univariate density f based on the sample of productivity indices of size N:

$$\hat{f}(x) = \frac{1}{Nh} \sum_{j=1}^{N} K\Big(\frac{x - \widehat{\mathcal{M}}_j}{h}\Big) \tag{17}$$

where j is the firm's subscript, $\widehat{\mathcal{M}}_j$ is its productivity index, x is the point of evaluation, h is the bandwidth (or window width, or smoothing parameter), and K is a symmetric monotone decreasing function that integrates to unity over the range of its argument, i.e., it satisfies $\int_{-\infty}^{+\infty} K(t)dt = 1$. The idea of kernel smoothing is to set a bandwidth that determines how near observations have to be in order to contribute to the average at each point.

This type of estimation involves two decisions, each with varying importance. The first is related to the choice of the kernel. For ease of computation, we chose the Gaussian kernel, which is given by:

$$K(t) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}t^2} \tag{18}$$

The most crucial decision, however, is that relating to the bandwidth, which determines the amount of smoothing. The higher the h is, the higher the smoothing, and the greater the loss of detail, and vice versa. There are several methods. We selected a hi-tech, plug-in second generation method, based on the study by Sheather and Jones (1991), who found that these methods have superior performance than first generation methods such as rules of thumb or least squares cross validation, as indicated by a more favorable balance between bias and variance.

B.2. Testing the closeness between productivity distributions

Given our overall nonparametric setting, we also consider nonparametric methods to explore the statistical differences between our productivity indicators, since they focus on the *entire* distributions instead of confining the comparison to summary statistics—such as the mean, in the case of the two-sample t-test, or the median, in the case of the Kruskal-Wallis test.

The test (Li, 1996) we consider in this paper is based on the generally accepted idea of measuring the global distance (closeness) between two densities $f(x)$ and $g(x)$ by the integrated squared error (Pagan and Ullah, 1999), namely:

$$\begin{aligned} I = I\big(f(x), g(x)\big) = \int_x \big(f(x) - g(x)\big)^2 dx &= \int_x \big(f^2(x) + g^2(x) - 2f(x)g(x)\big)dx \\ &= \int_x \big(f(x)dF(x) + g(x)dG(x) - 2g(x)dF(x)\big) \end{aligned} \tag{19}$$

where F and G would be two candidates for the distribution of X, with probability density functions $f(x)$ and $g(x)$. However, we may turn to kernel smoothing methods (Silverman, 1986) to estimate f, and therefore $\hat{f}$ would be the nonparametric kernel estimator of f. In such a case, since $\hat{f} = \big(1/(Nh)\big)\sum_{j=1}^{S} K\big((x_j - x)/h\big)$, a suitable estimator for I would be:

$$\begin{aligned} \tilde{I} &= \int_x \big(\hat{f}(x) - \hat{g}(x)\big)^2 dx \\ &= \frac{1}{N^2h}\sum_{j=1}^{S}\sum_{t=1}^{S}\Big[K\Big(\frac{x_j - x_t}{h}\Big) + K\Big(\frac{y_j - y_t}{h}\Big) - 2K\Big(\frac{y_j - x_t}{h}\Big) - K\Big(\frac{x_j - y_t}{h}\Big)\Big] \\ &\quad + \frac{1}{N^2h}\sum_{j=1}^{N}\Big[2K(0) - 2K\Big(\frac{x_j - y_j}{h}\Big)\Big] \end{aligned} \tag{20}$$

The integrated square error constitutes the basis to build the statistic on which the test is based (see Fan, 1994; Li, 1996; Pagan and Ullah, 1999), whose general form is:

$$T = \frac{Nh^{1/2}\tilde{I}}{\hat{\sigma}} \tag{21}$$

where

$$\hat{\sigma} = \frac{1}{N^2 h} \sum_{j=1}^{N} \sum_{t=1}^{N} \left[K\left(\frac{x_j - x_t}{h}\right) + K\left(\frac{y_j - y_t}{h}\right) + 2K\left(\frac{x_j - y_t}{h}\right) \right] \int K^2(\Psi) d\psi. \tag{22}$$

and h would be the bandwidth, window width or smoothing parameter, which we estimate using the plug-in method suggested by Sheather and Jones (1991).

References

Alam, I. M. S. (2001). A nonparametric approach for assessing productivity dynamics of large U.S. banks. *Journal of Money, Credit, and Banking*, 33(1):121–139.

Allen, F. and Santomero, A. M. (1998). The theory of financial intermediation. *Journal of Banking & Finance*, 21:1461–1485.

Allen, F. and Santomero, A. M. (2001). What do financial intermediaries do? *Journal of Banking & Finance*, 25:271–294.

Allen, L. and Rai, A. (1996). Operational efficiency in banking: An international comparison. *Journal of Banking & Finance*, 20(4):655–672.

Altunbaş, Y. and Chakravarty, S. P. (2001). Frontier cost functions and bank efficiency. *Economics Letters*, 72:233–240.

Altunbaş, Y., Gardener, E. P. M., Molyneux, P., and Moore, B. (2001). Efficiency in European banking. *European Economic Review*, 45:1931–1955.

Altunbaş, Y., Goddard, J., and Molyneux, P. (1999). Technical change in banking. *Economics Letters*, 64:215–221.

Altunbaş, Y. and Molyneux, P. (1996). Economies of scale and scope in European banking. *Applied Financial Economics*, 6:367–375.

Asmild, M., Paradi, J. C., Aggarwall, V., and Schaffnit, C. (2004). Combining DEA window analysis with the Malmquist index approach in a study of the Canadian banking industry. *Journal of Productivity Analysis*, 21(1):67–89.

Avkiran, N. K. (2000). Rising productivity of Australian trading banks under deregulation 1986–1995. *Journal of Economics and Finance*, 24(2):122–140.

Banker, R. D. (1993). Maximum likelihood, consistency and data envelopment analysis: a statistical foundation. *Management Science*, 39(10):1265–1273.

Bauer, P. W., Berger, A. N., and Humphrey, D. B. (1993). Efficiency and productivity growth in U.S. banking. In Fried, H. O., Lovell, C. A. K., and Schmidt, S. S., editors, *The Measurement of Productive Efficiency: Techniques and Applications*, pages 386–413. Oxford University Press, Oxford.

Berg, S., Førsund, F. R., Hjalmarsson, L., and Suominen, M. (1993). Banking efficiency in the Nordic countries. *Journal of Banking & Finance*, 17:371–388.

Berg, S. A., Bukh, P. N. D., and Førsund, F. R. (1995). Banking efficiency in the Nordic countries: A four-country Malmquist index analysis. Working paper, University of Aarhus, Denmark.

Berg, S. A., Førsund, F. R., and Jansen, E. S. (1992). Technical efficiency of Norwegian banks: The non-parametric approach to efficiency measurement. *Journal of Productivity Analysis*, 2:127–142.

Bergendahl, G. (1995). DEA and benchmarks for Nordic banks. Technical report, Gothenburg University, Gothenburg.

Berger, A. N., De Young, R., Genay, H., and Udell, G. F. (2000). Globalization of financial institutions: Evidence from cross-border banking performance. In Litan, R. E. and Santomero, A. M., editors, *Papers on Financial Services*, Economics, pages 23–158. Brookings Institution Press, Washington, D.C. http://brookings.nap.edu/books/0815752911/html/index.html.

Berger, A. N. and Humphrey, D. B. (1992). Measurement and efficiency issues in commercial banking. In Griliches, Z., editor, *Output Measurement in the Service Sectors*, pages 245–300. The University of Chicago Press, Chicago.

Berger, A. N. and Humphrey, D. B. (1997). Efficiency of financial institutions: International survey and directions for future research. *European Journal of Operational Research*, 98:175–212.

Bikker, J. A. (1999). Efficiency in the European banking industry: An exploratory analysis to rank countries. Research Series Supervision 18, De Nederlandsche Bank, Directorate Supervision. http://www.dnb.nl.

Bikker, J. A. (2002). Efficiency and cost differences across countries in a unified European banking market. DNB Staff Reports 87, De Nederlandsche Bank, Directorate Supervision. http://www.dnb.nl.

Bonin, J. P., Hasan, I., and Wachtel, P. (2005). Bank performance, efficiency and ownership in transition countries. *Journal of Banking & Finance*, 29(1):31–53.

Bos, J. W. B. and Schmiedel, H. (2003). Comparing efficiency in European banking: A metafrontier approach. http://hewpem.econ.upatras.gr/papers/BosSchmiedel.pdf.

Canhoto, A. M. and Dermine, J. (2003). A note on banking efficiency in Portugal, New vs. Old banks. *Journal of Banking & Finance*, 27(11):2087–2098.

Carbó, S., Gardener, E., and Williams, J. (2003). A note on technical change in banking: The case of European savings banks. *Applied Economics*, 35:705–719.

Casu, B. and Girardone, C. (2002). Efficiency of large banks in the Single European Market. ECONOMICS Discussion Papers 102, Middlesex University, London.

Casu, B. and Girardone, C. (2004). Financial conglomeration: efficiency, productivity and strategic drive. *Applied Financial Economics*, 4:687–696.

Casu, B., Girardone, C., and Molyneux, P. (2004). Productivity change in banking: A comparison of parametric and non-parametric approaches. *Journal of Banking & Finance*, 28(10):2521–2540.

Casu, B. and Molyneux, P. (2003). A comparative study of efficiency in European banking. *Applied Economics*, 35:1865–1876.

Cavallo, L. and Rossi, S. P. S. (2001). Scale and scope economies in the European banking systems. *Journal of Multinational Financial Management*, 11:515–531.

Cavallo, L. and Rossi, S. P. S. (2002). Do environmental variables affect the performance and technical efficiency of the European banking systems? A parametric analysis using the stochastic frontier approach. *The European Journal of Finance*, 8(1):123–146.

Caves, D. W., Christensen, L. R., and Diewert, W. E. (1982). The economic theory of index numbers and the measurement of input, output, and productivity. *Econometrica*, 50(6):1393–1414.

Chaffai, M. E., Dietsch, M., and Lozano-Vivas, A. (2001). Technological and environmental differences in the European banking industries. *Journal of Financial Services Research*, 19(2):147–162.

Daraio, C. and Simar, L. (2005a). Conditional nonparametric frontier models for convex and non convex technologies: a unifying approach. Discussion Paper DP0502, Institute de Statistique, Université Catholique de Louvain, Louvain-la-Neuve.

Daraio, C. and Simar, L. (2005b). A robust nonparametric approach to evaluate and explain the performance of mutual funds. *Journal of Productivity Analysis*, forthcoming.

Devaney, M. and Weber, W. L. (2000). Productivity growth, market structure, and technological change: evidence from the rural banking sector. *Applied Financial Economics*, 10:587–595.

Dietsch, M. and Lozano-Vivas, A. (2000). How the environment determines banking efficiency. A comparison between French and Spanish industries. *Journal of Banking & Finance*, 24:985–1004.

Efron, B. (1979). Bootstrap methods: Another look at the Jacknife. *Annals of Statistics*, 7:1–26.

Fan, Y. (1994). Testing the goodness-of-fit of a parametric density function by kernel method. *Econometric Theory*, 10:316–356.

Fan, Y. and Ullah, A. (1999). On goodness-of-fit tests for weekly dependent processes using kernel method. *Journal of Nonparametric Statistics*, 11:337–360.

Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society*, Ser.A,120:253–281.

Fecher, F. and Pestieau, P. (1993). Efficiency and competition in OECD financial services. In Fried, H. O., Lovell, C. A. K., and Schmidt, S. S., editors, *The Measurement of Productive Efficiency*, chapter 15, pages 374–385. Oxford University Press, Oxford.

Ferrier, G. D. and Hirschberg, J. D. (1997). Bootstrapping confidence intervals for linear programming efficiency scores: With an illustration using Italian banking data. *Journal of Productivity Analysis*, 8:19–33.

Färe, R., Grosskopf, S., and Lovell, C. A. K. (1994a). *Production Frontiers*. Cambridge University Press, Cambridge.

Färe, R., Grosskopf, S., Norris, M., and Zhang, Z. (1994b). Productivity growth, technical progress, and efficiency change in industrialized countries. *American Economic Review*, 84(1):66–83.

Fries, S. and Taci, A. (2005). Cost efficiency of banks in transition: Evidence from 289 banks in 15 post-communist countries. *Journal of Banking & Finance*, 29(1):55–81.

Fukuyama, H. (1995). Measuring efficiency and productivity growth in Japanese banking: a nonparametric frontier approach. *Applied Financial Economics*, 5:95–107.

Fukuyama, H. and Weber, W. L. (2002). Estimating output allocative efficiency and productivity change: Application to Japanese banks. *European Journal of Operational Research*, 137:177–190.

Gijbels, I., Mammen, E., Park, B., and Simar, L. (1999). On estimation of monotone and concave frontier functions. *Journal of the American Statistical Association*, 49 445:220–228.

Gilbert, R. A. and Wilson, P. W. (1998). Effects of deregulation on the productivity of Korean banks. *Journal of Economics and Business*, 50:133–155.

Gorton, G. and Rosen, R. (1995). Corporate control, portfolio choice, and the decline in banking. *Journal of Finance*, 50:1377–1419.

Grifell-Tatjé, E. and Lovell, C. A. K. (1995). A note on the Malmquist productivity index. *Economics Letters*, 47:169–175.

Grifell-Tatjé, E. and Lovell, C. A. K. (1999). Generalized malmquist productivity index. *Sociedad de Estadistica e Investigacion Operativa*, 7 1:81–101.

Grifell-Tatjé, E. and Lovell, C. A. K. (1996). Deregulation and productivity decline: The case of Spanish savings banks. *European Economic Review*, 40(6):1281–1303.

Grifell-Tatjé, E. and Lovell, C. A. K. (1997). The sources of productivity change in Spanish banking. *European Journal of Operational Research*, 98:365–381.

Grosskopf, S. (1993). Efficiency and productivity. In Fried, H. O., Lovell, C. A. K., and Schmidt, S. S., editors, *The Measurement of Productive Efficiency: Techniques and Applications*, chapter 4, pages 161–193. Oxford University Press, Oxford.

Grosskopf, S. (2003). Some remarks on productivity and its decompositions. *Journal of Productivity Analysis*, 20:459–474.

Harker, P. T. and Zenios, S. A. (2000). What drives the performance of financial institutions? In Harker, P. T. and Zenios, S. A., editors, *Efficiency of Financial Institutions: Efficiency, Innovation, Regulation*, chapter 1, pages 3–31. Cambridge University Press, Cambridge.

Humphrey, D. B. (1992). Flow versus stock indicators of banking output: Effects on productivity and scale economy measurement. *Journal of Financial Services Research*, 6:115–135.

Humphrey, D. B. (1993). Cost and technical change: Effects from bank deregulation. *Journal of Productivity Analysis*, 4:9–34.

Isik, I. and Hassan, M. K. (2003a). Financial deregulation and total factor productivity change: An empirical study of Turkish commercial banks. *Journal of Banking & Finance*, 27:1455–1485.

Isik, I. and Hassan, M. K. (2003b). Financial disruption and bank productivity: The 1994 experience of Turkish banks. *The Quarterly Review of Economics and Finance*, 43:291–320.

Kasman, A., Kirbas-Kasman, S., and Carvallo, O. (2005). Efficiency and foreign ownership in banking: an international comparison.

Kneip, A., Park, B. U., and Simar, L. (1998). A note on the convergence of nonparametric dea estimators for production efficiency scores. *Econometric Theory*, 14:783–793.

Kneip, A., Simar, L., and Wilson, P. W. (2003). Asymptotics for DEA estimators in non-parametric frontier models. Discussion Paper 0317, Institut de Statistique, Université Catholique de Louvain, Louvain-la-Neuve.

Korostelev, A., Simar, L., and Tsybakov, A. B. (1995). On estimation of monotone and convex boundaries. *Pub. Inst. Stat. Univ. Paris*, XXXIX(1):3–18.

Kumbhakar, S. C., Lozano-Vivas, A., Lovell, C. A. K., and Hasan, I. (2001). The effects of deregulation on the performance of financial institutions: The case of Spanish savings banks. *Journal of Money, Credit, and Banking*, 33(1):101–120.

Li, Q. (1996). Nonparametric testing of closeness between two unknown distribution functions. *Econometric Reviews*, 15:261–274.

Lozano-Vivas, A., Pastor, J. T., and Hasan, I. (2001). European bank performance beyond country borders: What really matters? *European Finance Review*, 5(1–2):141–165.

Lozano-Vivas, A., Pastor, J. T., and Pastor, J. M. (2002). An efficiency comparison of European banking systems operating under different environmental conditions. *Journal of Productivity Analysis*, 18(1):59–77.

Maggi, B. and Rossi, S. P. S. (2003). An efficiency analysis of banking systems: A comparison of European and United States large commercial banks using different functional forms. Working Paper 0306, Department of Economics, University of Vienna, Vienna. http://www.univie.ac.at/Wirtschaftswissenschaften/.

Maudos, J. and Pastor, J. M. (2000). La eficiencia del sistema bancario español en el contexto de la Unión Europea. *Papeles de Economía Española*, 0(84–85):155–168.

Maudos, J. and Pastor, J. M. (2001). Cost and profit efficiency in banking: An international comparison of Europe, Japan and USA. *Applied Economics Letters*, 8(6):383–387.

Maudos, J., Pastor, J. M., Pérez, F., and Quesada, J. (2002). Cost and profit efficiency in European banks. *Journal of International Financial Markets, Institutions, and Money*, 12(1):33–58.

Molyneux, P. (2002). Technical change, costs and profits in European Banking. Working Paper 03–21, United Nations University, Tokyo.

Mukherjee, K., Ray, S. C., and Miller, S. M. (2001). Productivity growth in large US commercial banks: The initial post-deregulation experience. *Journal of Banking & Finance*, 25:913–939.

Noulas, A. G. (1997). Productivity growth in the Hellenic banking industry: State versus private banks. *Applied Financial Economics*, 7:223–228.

Pagan, A. and Ullah, A. (1999). *Nonparametric Econometrics*. Themes in modern econometrics. Cambridge University Press, Cambridge.

Pastor, J. M. (2002). Credit risk and efficiency in the European banking system: A three-stage analysis. *Applied Financial Economics*, 12:895–911.

Pastor, J. M., Pérez, F., and Quesada, J. (1997). Efficiency analysis in banking firms: An international comparison. *European Journal of Operational Research*, 98:395–407.

Pastor, J. M. and Serrano, L. (2005a). The effect of specialization on bank's efficiency: An international comparison. *International Review of Applied Economics*, forthcoming.

Pastor, J. M. and Serrano, L. (2005b). Efficiency, endogenous and exogenous credit risk in the banking systems of the Euro area. *Applied Financial Economics*, forthcoming.

Quah, D. T. (1995). Regional convergence clusters across europe. Discussion Paper 274, CEPR.

Rogers, K. E. (1998). Nontraditional activities and the efficiency of U.S. commercial banks. *Journal of Banking & Finance*, 22:467–482.

Rogers, K. E. and Sinkey Jr, J. F. (1999). An analysis of nontraditional activities at U.S. commercial banks. *Review of Financial Economics*, 8:25–39.

Schure, P., Wagenvoort, R., and O'Brien, D. (2004). The efficiency and the conduct of European banks: Developments after 1992. *Review of Financial Economics*, 13(4):371–396.

Sengupta, J. K. (1982). Efficiency measurement in stochastic input-output systems. *International Journal of Systems Science*, 13:273–287.

Sheather, S. J. and Jones, M. C. (1991). A reliable data-based bandwidth selection method for kernel density estimation. *Journal of the Royal Statistical Society*, Ser.B,53(3):683–690.

Silverman, B. W. (1986). *Density Estimation for Statistics and Data Analysis*. Chapman and Hall, London.

Simar, L. (1992). Estimating efficiencies from frontier models with panel data: a comparison of parametric non-parametricand semi-parametric methods with bootstrapping. *Journal of Productivity Analysis*, 3:167–203.

Simar, L. and Steinmann, L. (2003). On the comparability of efficiency scores in nonparametric frontier models. Discussion Paper 0318, Institut de Statistique, Université Catholique de Louvain, Louvain-la-Neuve.

Simar, L. and Wilson, P. (1998a). Productivity growth in industrialized countries. Discussion Paper 9836, Institut de Statistique, Universite Catholique de Louvain, Louvain la Neuve, Belgium.

Simar, L. and Wilson, P. (1998b). Sensitivity analysis of efficiency scores: How to bootstrap in nonparametric frontier models. *Management Science*, 44:49–61.

Simar, L. and Wilson, P. W. (1998c). Sensitivity analysis of efficiency scores: How to bootstrap in nonparametric frontier models. *Management Science*, 44(1):49–61.

Simar, L. and Wilson, P. W. (1999). Estimating and bootstrapping Malmquist indices. *European Journal of Operational Research*, 115:459–471.

Simar, L. and Wilson, P. W. (2000a). A general methodology for bootstrapping in nonparametric frontier models. *Journal of Applied Statistics*, 27(6):779–802.

Simar, L. and Wilson, P. W. (2000b). Statistical inference in nonparametric frontier models: The state of the art. *Journal of Productivity Analysis*, 13(1):49–78.

Simar, L. and Wilson, P. W. (2003). Estimation and inference in two-stage, semi-parametric models of production processes. Technical Report TR0310, IAP Statistics Network, Institut de Statistique, Université Catholique de Louvain, Louvain-la-Neuve.

Simar, L. and Zelenyuk, V. (2003). Statistical inference for aggregates of Farrell-type effieciencies. Discussion Paper 0324, Institut de Statistique, Université Catholique de Louvain, Louvain-la-Neuve.

Stavárek, D. (2003a). Banking efficiency in Visegrad countries before joining the European Union. Finance Working Paper 0312010, WUSTL, Washington.

Stavárek, D. (2003b). European banking efficiency: A cross-country analysis of transition and developed banking sectors. In *Proceedings of the Fifth International Conference Aidea Giovani: Information, Markets and Firms*, Milano. Universita Cattolica del Sacro Cuore.

Stiroh, K. J. (2000). How did bank holding companies prosper in the 1990s? *Journal of Banking & Finance*, 24:1703–1745.

Tirtiroglu, D., Daniels, K. N., and Tirtiroglu, E. (1998). Total fator productivity growth and regulation in U.S. commercial banking during 1946–1995: An empirical investigation. *Journal of Economics and Business*, 50:171–189.

Tortosa-Ausina, E., Grifell-Tatjé, E., Armero, C., and Conesa, D. (2003). Sensitivity analysis of efficiency and Malmquist productivity indices: An application to Spanish savings banks. Working Paper 2003/02, Centre for Applied Economic Research (CAER), University of New South Wales, Sydney. http://economics.web.unsw.edu.au/research/caer/.

Tsionas, E. G., Lolos, S. E. G., and Christopoulos, D. K. (2003). The performance of the Greek banking system in view of the EMU: Results from a non-parametric approach. *Economic Modelling*, 20:571–592.

Vander Vennet, R. (2002). Cost and profit efficiency of financial conglomerates and universal banks in Europe. *Journal of Money, Credit, and Banking*, 34(1):254–282.

Weill, L. (2003a). Banking efficiency in transition economies. *Economics of Transition*, 11(3):569–592.

Weill, L. (2003b). Is there a lasting gap in bank efficiency between Eastern and Western European countries? http://www.univ-orleans.fr/DEG/GDRecomofi.

Weill, L. (2004). Measuring cost efficiency in European banking: A comparison of frontier techniques. *Journal of Productivity Analysis*, 21:133–152.

Wheelock, D. C. and Wilson, P. W. (1999). Technical progress, inefficiency, and productivity change in US banking, 1984–1993. *Journal of Money, Credit, and Banking*, 31(2):212–234.

Williams, J. (2004). Determining management behaviour in European banking. *Journal of Banking & Finance*, forthcoming.

Williams, J. and Gardener, E. P. M. (2003). The efficiency of European regional banking. *Regional Studies*, 37(4):321–330.

Worthington, A. C. (1999). Malmquist indices of productivity change in Australian financial services. *Journal of International Financial Markets, Institutions and Money*, 9:303–320.

FUNDACIÓN DE LAS CAJAS DE AHORROS

DOCUMENTOS DE TRABAJO

Últimos números publicados

159/2000 Participación privada en la construcción y explotación de carreteras de peaje
Ginés de Rus, Manuel Romero y Lourdes Trujillo

160/2000 Errores y posibles soluciones en la aplicación del *Value at Risk*
Mariano González Sánchez

161/2000 Tax neutrality on saving assets. The spahish case before and after the tax reform
Cristina Ruza y de Paz-Curbera

162/2000 Private rates of return to human capital in Spain: new evidence
F. Barceinas, J. Oliver-Alonso, J.L. Raymond y J.L. Roig-Sabaté

163/2000 El control interno del riesgo. Una propuesta de sistema de límites riesgo neutral
Mariano González Sánchez

164/2001 La evolución de las políticas de gasto de las Administraciones Públicas en los años 90
Alfonso Utrilla de la Hoz y Carmen Pérez Esparrells

165/2001 Bank cost efficiency and output specification
Emili Tortosa-Ausina

166/2001 Recent trends in Spanish income distribution: A robust picture of falling income inequality
Josep Oliver-Alonso, Xavier Ramos y José Luis Raymond-Bara

167/2001 Efectos redistributivos y sobre el bienestar social del tratamiento de las cargas familiares en el nuevo IRPF
Nuria Badenes Plá, Julio López Laborda, Jorge Onrubia Fernández

168/2001 The Effects of Bank Debt on Financial Structure of Small and Medium Firms in some European Countries
Mónica Melle-Hernández

169/2001 La política de cohesión de la UE ampliada: la perspectiva de España
Ismael Sanz Labrador

170/2002 Riesgo de liquidez de Mercado
Mariano González Sánchez

171/2002 Los costes de administración para el afiliado en los sistemas de pensiones basados en cuentas de capitalización individual: medida y comparación internacional.
José Enrique Devesa Carpio, Rosa Rodríguez Barrera, Carlos Vidal Meliá

172/2002 La encuesta continua de presupuestos familiares (1985-1996): descripción, representatividad y propuestas de metodología para la explotación de la información de los ingresos y el gasto.
Llorenc Pou, Joaquín Alegre

173/2002 Modelos paramétricos y no paramétricos en problemas de concesión de tarjetas de credito.
Rosa Puertas, María Bonilla, Ignacio Olmeda

174/2002 Mercado único, comercio intra-industrial y costes de ajuste en las manufacturas españolas.
José Vicente Blanes Cristóbal

175/2003 La Administración tributaria en España. Un análisis de la gestión a través de los ingresos y de los gastos.
Juan de Dios Jiménez Aguilera, Pedro Enrique Barrilao González

176/2003 The Falling Share of Cash Payments in Spain.
Santiago Carbó Valverde, Rafael López del Paso, David B. Humphrey
Publicado en "Moneda y Crédito" nº 217, pags. 167-189.

177/2003 Effects of ATMs and Electronic Payments on Banking Costs: The Spanish Case.
Santiago Carbó Valverde, Rafael López del Paso, David B. Humphrey

178/2003 Factors explaining the interest margin in the banking sectors of the European Union.
Joaquín Maudos y Juan Fernández Guevara

179/2003 Los planes de stock options para directivos y consejeros y su valoración por el mercado de valores en España.
Mónica Melle Hernández

180/2003 Ownership and Performance in Europe and US Banking – A comparison of Commercial, Co-operative & Savings Banks.
Yener Altunbas, Santiago Carbó y Phil Molyneux

181/2003 The Euro effect on the integration of the European stock markets.
Mónica Melle Hernández

182/2004 In search of complementarity in the innovation strategy: international R&D and external knowledge acquisition.
Bruno Cassiman, Reinhilde Veugelers

183/2004 Fijación de precios en el sector público: una aplicación para el servicio municipal de suministro de agua.
Mª Ángeles García Valiñas

184/2004 Estimación de la economía sumergida es España: un modelo estructural de variables latentes.
Ángel Alañón Pardo, Miguel Gómez de Antonio

185/2004 Causas políticas y consecuencias sociales de la corrupción.
Joan Oriol Prats Cabrera

186/2004 Loan bankers' decisions and sensitivity to the audit report using the belief revision model.
Andrés Guiral Contreras and José A. Gonzalo Angulo

187/2004 El modelo de Black, Derman y Toy en la práctica. Aplicación al mercado español.
Marta Tolentino García-Abadillo y Antonio Díaz Pérez

188/2004 Does market competition make banks perform well?.
Mónica Melle

189/2004 Efficiency differences among banks: external, technical, internal, and managerial
Santiago Carbó Valverde, David B. Humphrey y Rafael López del Paso

190/2004 Una aproximación al análisis de los costes de la esquizofrenia en españa: los modelos jerárquicos bayesianos
F. J. Vázquez-Polo, M. A. Negrín, J. M. Cavasés, E. Sánchez y grupo RIRAG

191/2004 Environmental proactivity and business performance: an empirical analysis
Javier González-Benito y Óscar González-Benito

192/2004 Economic risk to beneficiaries in notional defined contribution accounts (NDCs)
Carlos Vidal-Meliá, Inmaculada Domínguez-Fabian y José Enrique Devesa-Carpio

193/2004 Sources of efficiency gains in port reform: non parametric malmquist decomposition tfp index for Mexico
Antonio Estache, Beatriz Tovar de la Fé y Lourdes Trujillo

194/2004 Persistencia de resultados en los fondos de inversión españoles
Alfredo Ciriaco Fernández y Rafael Santamaría Aquilué

195/2005 El modelo de revisión de creencias como aproximación psicológica a la formación del juicio del auditor sobre la gestión continuada
Andrés Guiral Contreras y Francisco Esteso Sánchez

196/2005 La nueva financiación sanitaria en España: descentralización y prospectiva
David Cantarero Prieto

197/2005 A cointegration analysis of the Long-Run supply response of Spanish agriculture to the common agricultural policy
José A. Mendez, Ricardo Mora y Carlos San Juan

198/2005 ¿Refleja la estructura temporal de los tipos de interés del mercado español preferencia por la liquidez?
Magdalena Massot Perelló y Juan M. Nave

199/2005 Análisis de impacto de los Fondos Estructurales Europeos recibidos por una economía regional: Un enfoque a través de Matrices de Contabilidad Social
M. Carmen Lima y M. Alejandro Cardenete

200/2005 Does the development of non-cash payments affect monetary policy transmission?
Santiago Carbó Valverde y Rafael López del Paso

201/2005 Firm and time varying technical and allocative efficiency: an application for port cargo handling firms
Ana Rodríguez-Álvarez, Beatriz Tovar de la Fe y Lourdes Trujillo

202/2005 Contractual complexity in strategic alliances
Jeffrey J. Reuer y Africa Ariño

203/2005 Factores determinantes de la evolución del empleo en las empresas adquiridas por opa
Nuria Alcalde Fradejas y Inés Pérez-Soba Aguilar

204/2005 Nonlinear Forecasting in Economics: a comparison between Comprehension Approach versus Learning Approach. An Application to Spanish Time Series
Elena Olmedo, Juan M. Valderas, Ricardo Gimeno and Lorenzo Escot

205/2005 Precio de la tierra con presión urbana: un modelo para España
Esther Decimavilla, Carlos San Juan y Stefan Sperlich

206/2005 Interregional migration in Spain: a semiparametric analysis
Adolfo Maza y José Villaverde

207/2005 Productivity growth in European banking
Carmen Murillo-Melchor, José Manuel Pastor y Emili Tortosa-Ausina