Productivity growth in European banking*

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Abstract

This article analyzes productivity growth for European banks over the 1995–2001 period. Contrary 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 sheds 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

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1. Introduction

The turmoil which has been affecting the European banking industry over the last two decades or so seems far from quitting yet. Although main deregulatory initiatives took place in the eighties, in the recent years there are 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., that have contributed significantly to re-shape the European Union (EU)[1] banking industries, 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 in recent times, 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 of 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 investigating whether 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 at improving 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 its 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.

This point is of paramount relevance when delving into the underpinnings of our database. Although it contains the most important institutions in each banking industry, some of them are absent, jeopardizing the reliability of our results. Obviously, previous studies on the efficiency and productivity of the banking systems of the European Union are jeopardized in the same way. Yet our study contributes to address the shortcoming thanks to the methodology we employ, whose re-sampling features are very appreciated when there are missing data for some firms. In such a case, bootstrapping techniques become much more informative than in those other circumstances in which the whole sample is available, granting us with the possibility to conduct statistical inference and, therefore, to draw much more painstaking conclusions. This constitutes further a contribution, provided 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.

This contribution is further understood when realizing our sample of financial institutions is so-

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

mewhat *arbitrary*, since, althought the sample is highly representative, it is composed by those firms for which it was possible to collect consistent data over the period.[2] Consequently, the results could 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 this technique turns out to be very 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 most populated countries in the European Union, namely, France, Germany, Italy, Spain, and the United Kingdom, ours considers a much broader database in terms of nations, as we consider all EU members but Greece, constituting therefore a database of 14 countries—excepting also the ten new members who joined the EU in 2004. Finally, our years of study are also of interest, uncovering the recent period 1995–2001.

We also make an attempt to disentangle some of the sources as to 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 as to why EU financial markets are so segmented, which is still highly intriguing, both on the supply—savings behavior—and the demand sides—the behavior of firms. For this, we consider nonparametric methods, as opposed to most previous studies which analyze the likely determinants of efficiency or productivity using either OLS or censored regression models—therefore being somewhat inconsistent, as nonparametric methods are used in their first-stage analysis and parametric methods are used in the second stage.

The plan of the paper is to begin with some review of 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 ensuing Section is devoted to present data and to define inputs and outputs (Section 4). Finally, Section 5 presents the most relevant results, along with some ideas about the likely impact of country-specific related variables on productivity.

2. Literature review

2.1. Previous literature on international comparisons of bank efficiency

The literature on international comparisons of bank efficiency and productivity has 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 Stochastic Frontier Approach (SFA) or Distribution Free Approach (DFA)—or nonparametric methods—mostly Data Envelopment Analysis (DEA)—is roughly balanced in its numbers.

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

The 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 so as to measure the efficiency of the Nordic banking industries. More recently, Lozano-Vivas *et al.* (2001) and Lozano-Vivas *et al.* (2002) applied also nonparametric techniques to compare technical efficiency in ten European banking industries for year 1993 correcting for environmental variables. Pastor (2002) used also DEA to analyze the 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, analyzing also their determinants. Finally, Pastor and Serrano (2003) analyze cost efficiency for nine European countries over the 1992–1998 period, isolating that inefficiency entirely attributable to specialization.

Some 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 estimating cross-border banking cost and profit efficiency. Likewise, Dietsch and Lozano-Vivas (2000) investigate the influence that environmental conditions have on the cost efficiency of French and Spanish banking industries during 1988–1992. Maudos and Pastor (2000) use also 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. Maudos *et al.* (2002) analyze using a random effects model and a fixed effects model—along with DFA—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 the cost efficiency, along with scale and scope economies, for a sample of commercial banks for fifteen European countries and the U.S. during the 1995–1998 period, checking the stability and the robustness of their results across different specifications. Finally, Pastor and Serrano (2005) analyze risk -adjusted cost and profit efficiency measures for a set of European banking systems using DFA obtaining that adjusting for risk is important specially in the case of profit efficiency.

Finally, there is a third group of relatively recent papers devoted to the international comparison of bank efficiency that use Stochastic Frontier Approach (SFA). 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 specification and the Fourier one 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 of fifteen European countries between 1989 and 1997. Maudos and Pastor (2001) analyze cost and profit efficiency for a sample of sixteen countries (fourteen of 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, yet not in Japan. In the same way, Cavallo and Rossi (2001, 2002), using also SFA, analyze the cost efficiency of a sample of six OECD countries during 1992-1997. The results confirm that recent regulatory changes have contributed to increase the optimal scale. Likewise, Bikker (2002), using SFA, seeks to discover the level and spread of bank cost efficiency of 15 European countries in the EU founding 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 of seventeen European countries, finding that conglomerates are more revenue efficiency than their specialized competitors and that the degree of both cost and profit efficiency is higher in universal banks 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, obtaining that technical change has reduced total cost of European banks at an average rate of 3.8% per year, meanwhile has reduced profit at 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, there are a set of papers devoted to analyze the performance of Eastern banking sistems. So Weill (2003a) compares the efficiency of banks from 17 Western European countries and six Eastern European countries to assess the performance gap between both groups of banks, testing also the possible influence of environmental variables and risk preferences on the efficiency gap. The results show that there is a gap in bank efficiency between Eastern and Western European countries. In other study, Weill (2003b) compare the performance of foreign-owned and domestic-owned banks operating in the Czech Republic and Poland, using several approaches, DEA, SFA and DFA, finding that on average foreign-owned banks are more efficiency than domestic-owned banks. Bonin *et al.* (2005) investigate the effects of ownership on bank efficiency for eleven transition countries for the period 1996–2000 finding that foreign-owned banks are more cost-efficient than other banks. Similarly, Fries and Taci (2005) analyze cost efficiency of 15 East 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 of six European countries between 1990 and 1998 suggesting that the most pressing management problem for European saving banks is bad management. Finally, Schure *et al.* (2004) assess the efficiency of the European banking sector in the period 1993–97 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 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 into biased estimation in the presence of inefficiency. 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 use 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); Fukuyama and Weber (2002) examined the efficiency and productivity growth in the Japanese banking industry for the 1989–1991 and 1993–1996 period 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 (2004b) evaluates productivity change of Italian financial conglomerates during 1996-99 using both parametric and nonparametric approaches. Canhoto and Dermine (2003) quantify the magnitude of efficiency gains and TFP growth of Portuguese banks for 1990–1995. Special attention deserves the study by Berg *et al.* (1992), since it was the first one using MPI to analyze productivity growth during the deregulation in 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 are dedicated to analyze particular banking systems. The studies devoted to international comparisons of banking productivity are much fewer, barely two. Firstly 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 pointing out that, indeed, the index was not suggested by Sten Malmquist himself but by Caves *et al.* (1982).

Yet the most recent contribution on this issue is the study by Casu *et al.* (2004) that use MPI and parametric techniques to analyze the 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 because of the highly nonlinear way in which the 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). The absence of an indicator of statistical significance reduces the reliability and usefulness of the results.

Some authors have used bootstrapping techniques so as to construct confidence intervals for the efficiency scores and productivity indices in order to address the main shortcoming of the DEA-MPI approach. The first study is the one by Ferrier and Hirschberg (1997), who measured technical efficiency for Italian banks for 1986. Regarding productivity change, there are only three studies blending MPI and bootstrapping techniques. The first one 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 one 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) devoted to 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 are devoted to analyze the productivity growth at the international level, and none of them uses bootstrapping to address the problem of the 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 kind 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: first, the data give a good approximation of the production function. Second, 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 random structure of the model does not discriminate among inefficiency and other

[5]Other studies, instead of analyzing productivity change over time, compare the productivity differences among some 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 those parametric methods such as SFA require to be met.

sources of randomness.[7] 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. However the difficulty was greater when, in order to construct confidence intervals, the aim was to obtain the asymptotic distribution of the efficiency estimators. Gijbels *et al.* (1999), obtained its sampling distribution for one input and one output but in the case of the multi-input multi-output setup, a bootstrap mechanism appears to be the only feasible alternative. In this sense, Simar and Wilson (1998b) have designed a bootstrap mechanism that approximates the distribution of efficiency.

With regard to the MPI, the lack of statistical properties of the efficiency will be transferred to it since the DEA estimates are exclusively the components of the index. Therefore, and in order to solve the previous problem but in the productivity framework, Simar and Wilson (1998a, 1999) have adapted the bootstrap procedure for technical efficiency to discern among significant and nonsignificant changes in productivity. Along this Section we firstly introduce a brief review of both efficiency measurement and bootstrap procedure and secondly apply them to the productivity analysis.

3.1. Bootstrapping DEA Estimates

Let consider, at time t, an economic sector where N firms produce q outputs from p inputs whom we may define, following Simar and Wilson's (1998b) notation, the next set of feasible input-output combination,

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

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 unidentified as well. The estimation of efficiency and the analysis of its resulting accuracy in a nonparametric setup require to introduce some assumptions on the Data Generating Process (DGP). In other words, from

[7] When this detriment was addressed by some researchers, Sengupta (1982) began to look at stochastic issues. Notwithstanding the statistical foundation of the DEA estimator was provided by Simar (1992) and Banker (1993).

an unknown population we have to identify the distribution function from which to draw random samples as $X = \{(\boldsymbol{x}_j, \boldsymbol{y}_j)\}_{j=1}^N$. The selection of DEA as the estimation method for efficiency requires incorporating 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, 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 constant returns to scale assumption into the benchmark technology while the two first 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

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

The properties of $\widehat{\theta}(\boldsymbol{x}_j, \boldsymbol{y}_j)$ depend on the unknown distribution function whom it can be drawn random samples; moreover, the accuracy of the estimation requires to know the distribution function of the estimator or at least its mean and its 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, estimate $\theta = t(F)$ by the same principle: $\widehat{\theta} = t(F_N)$. This bootstrap distribution can be approximated by Monte Carlo simulations provided that, first the variability of the efficiency when sampling from F can be approximated by the statistic variability when resampling from F_N and secondly, it is allowed to extract any values of the statistical by resampling from F_N.

In the efficiency framework, Simar and Wilson (1998b)[8] have proposed a bootstrap procedure consisting on the generation of B samples as $X^* = \{(\boldsymbol{x}_j^*, \boldsymbol{y}_j^*)\}_{j=1}^N$ by mimicking the DGP defined above (see Simar and Wilson, 2000a, for a complete description of the algorithm) and for each firm

[8]Simar and Wilson procedure has proved to solve the inconsistent problems of other applications as the use of a naive bootstrap, moreover it has solved the absence of probability mass beyond the upper bound of efficiency (one) by the reflection method of Silverman (1986).

and for each of these B samples, the bootstrap value of efficiency can be estimated by DEA as:

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

Thus we obtain the empirical distribution of 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 a 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 $\theta(\boldsymbol{x}_j, \boldsymbol{y}_j)$ and thence $B^{-1}\sum_{b=1}^B \widehat{\theta}_b^*(\boldsymbol{x}_j, \boldsymbol{y}_j)$ will be a downward-biased estimator of $\widehat{\theta}(\boldsymbol{x}_j, \boldsymbol{y}_j)$.

The bias can be calculated, then, 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 $\widehat{\widehat{\theta}}(\boldsymbol{x}_j, \boldsymbol{y}_j) = \widehat{\theta}(\boldsymbol{x}_j, \boldsymbol{y}_j) - \widehat{bias}$ provides us the corrected estimator.

Confidence intervals for the efficiency of each firm can be estimated via the percentile confidence interval by the following value,

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

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 whether 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 Malmquist productivity index was introduced by Caves *et al.* (1982). The index 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) and $\widehat{\theta}_{t_2}^{t_1} = \widehat{\theta}^{t_1}(\boldsymbol{x}_j^{t_2}, \boldsymbol{y}_j^{t_2})$ 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[9] for a sample of period t_2 when the frontier is the one of period t_1.

Malmquist index in Equation (11) can be read in the following way: a firm j has improved productivity from t_1 to t_2 when $\widehat{\mathcal{M}}_j(t_1, t_2) < 1$, on the contrary, its productivity has decreased when

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

the index is greater than one; and finally, when $\widehat{\mathcal{M}}_j(t_1, t_2) = 1$ the productivity has not changed in the period.

One of the main advantages of the Malmquist index in this framework, is that it can be rewritten and decomposed into different indices in order to analyze the different sources of change in productivity. The first and simplest decomposition was proposed by Färe *et al.* (1995) and it separates productivity change into changes in efficiency (catching-up) and changes in frontiers (technical change). Since then, new decompositions have been developed (see Grifell-Tatjé and Lovell, 1999, for a review of them and of their properties), all of them focus attention on a more exhaustive decomposition of productivity change than the proposed by Färe *et al.* (1995). However in our paper we have applied the former due to its simplicity may stand for advantage in terms of significance results.[10] 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 ($\widehat{EC}_j(t_1, t_2)$) shows how productivity changes due to the 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 of both indices are greater, less or equal to one, and their interpretations are analogous to those provided for productivity change.

The application of the DEA estimates in the construction of the change indices transfers them the lack of statistical properties of the efficiency. That is to say, it is unknown whether the indices in Equation (13) were obtained due to sampling variability or to significant results. In order to solve this drawback, and as in the case of technical efficiency, Simar and Wilson (1998a, 1999) have adapted the bootstrap procedure explained in the previous Section to the Malmquist index. In this case the algorithm generates bootstrap efficiencies preserving the temporal correlation of the data by exchanging the distributional function for a bivariate kernel estimator of density. In practice, the bootstrap procedure diverges slightly from the previous and the main change is the resampling procedure: we resample in pairs of efficiency values for two consecutive years instead of resampling in the single efficiency values.

The empirical distribution of each index for each firm

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

is obtained by estimating, as in Equation (9), the efficiencies of the Malmquist and its decomposed indices of Equation (13) for two consecutive years and by repeating this process B times. As in the

[10]An exhaustive decomposition of MPI, as in Simar and Wilson (1998a), may imply that although the change in productivity would be significant the sources of productivity could turn nonsignificant themselves.

previous section, the bias estimator of each change index can be obtained by:[11]

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

Likewise, we construct the bias corrected estimator $\hat{\widehat{\mathcal{M}}}_j(t_1,t_2)$ by removing the estimated bias of Equation (15): $\hat{\widehat{\mathcal{M}}}_j(t_1,t_2) = \widehat{\mathcal{M}}_j(t_1,t_2) - \widehat{bias}\{\widehat{\mathcal{M}}_j(t_1,t_2)\}$ and, equally to Equation (10), we 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 of $\widehat{\mathcal{M}}_j(t_1,t_2)$; i.e., the presence of the unity in the interval (16) is interpreted as a non significantly different from unity value of $\widehat{\mathcal{M}}_j(t_1,t_2)$. However, if unity is not in 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 must be very careful in the selection of data. Not only the possible accounting heterogeneity of the variables used has to be considered, but also the different specializations and the different environment. In this study the data base was obtained from Bankscope, which provides homogenous information of banks of different countries and classifies banks in terms of specialization, so that the 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 those 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.

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 some other outputs accounting for the nontraditional activities most banks are

[11] We illustrate only the case of the Malmquist productivity index but the procedure is identical for each of the decomposed index.

currently engaged in (Allen and Santomero, 1998, 2001; Rogers and Sinkey Jr, 1999) and which may influence efficiency (Rogers, 1998).

Accordingly, for the inputs choice we face a broad consensus and, therefore, our choice is free from controversy. Specifically, it encompasses labour (x_1), measured by total labour 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 one 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 different output definition approaches. It would be desirable to disaggregate it, but the lack of painstaking 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 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

5.1. Productivity growth and its decomposition

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 considering all firms together, i.e., the entire EU-14 banking firms in our sample. Results are also split into different ways. First, productivity change sources are decomposed following Grosskopf (1993) into its 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 joined the EU by 1995, since it could help disentangling what the effects of their 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.[12] In particular, we use single asterisks (*) to indicate those entries 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 below unity indicate **productivity growth**, whereas those greater than one indicate **productivity**

[12] When averaging bank estimates for a country, we also average the corresponding bootstrap values for the same banks in order to obtain estimates of significance for the country.

decline.[13] 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. Likewise productivity, all those entries without asterisks indicate 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 involve simultaneously technical regress and efficiency gains, or technical progress and efficiency losses.[14]

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 among both subperiods 1995–1998 and 1998–2001 considering all firms and countries together. By 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 involved simultaneously 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 suffered significant productivity decline. More specifically, the cases of The Netherlands and Sweden combine simultaneously significant technical regress with efficiency decrease, meanwhile 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, the 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.[15] The annual figures suggest 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.

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 bunch of meaningful information

[13]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.

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

[15]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 period.

both at country and, especially, at the *firm* level. In particular, application of the bootstrap allows assessing whether 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, one can elucidate that the corresponding index is significantly different from unity. A summary of results on significance is reported on 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 those 222 firms going through productivity decline, only in 20 instances it was not significant—and in two cases it was significant at the 10% significance level.

Considering technical change, we find that overall productivity growth experience at EU level during 1995–2001 has been brought about by 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—adding to 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 period 1995–2001; in 19 instances, however, efficiency losses were not found to be significant.

Our results are not exactly coincidental with those obtained by previous studies analyzing productivity growth in European banks. In their study, Casu *et al.* (2004) find Spain and Italy are 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 these are the banks experiencing faster productivity growth.

These results, far from being disappointing, help to triangulate those obtained by 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 by 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 yet rather on a

European Union basis. Notwithstanding there exists some evidence (Chaffai *et al.*, 2001; Dietsch and Lozano-Vivas, 2000) suggesting 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.[16] 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 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 can 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.

Indeed, 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 attempting to ascertain the (likely) determinants of efficiency and/or productivity. Most of these two-stage studies have remarkable disadvantages, put 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) for disentangling what determines the results obtained in the first stage. This constitutes not only an inconsistency in itself. Besides, 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 fix 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 differently. 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 upon 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 EU help explain the observed discrepancies amongst European banks. Thus, this Section would ask questions such as how integrated European banking systems have become (or if they are still like isolated islands), how much

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

does knowing the host country's banking productivity explain the bank's, how much does knowing that of surrounding countries help explain the bank's, or even how much does knowing that of those countries which joined the EU at the same time explain it (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 as in the $\widehat{\mathcal{M}}_j^c$ we would be conditioning on host nation-state information. Once these series were calculated, we would 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 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 found multi-modality, it could entail 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 underwent by European banking systems has been the primary force driving productivity growth in European banking. If that were the case, i.e., if each bank's productivity index is similar to that of other banks in other countries, densities should be concentrated around the unity—since we divided by EU-14 geometric mean. If the trend were to continue, probability mass should concentrate more tightly over time—i.e., for period 1998–2001.

We also consider European banking systems are not like isolated islands. Accordingly, each bank's performance could be predicted by that both in surrounding countries and the host state (Quah, 1995). In this case, we would 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 would be constructed by dividing the productivity index obtained for each bank by the average of those banks in its home country and its economic neighborhood countries.[17] 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 taking together all European countries, although the likely scenarios here could be multiple as well.

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 those banks in countries which joined the EU simultaneously.[18] Therefore, if densities corresponding to $\widehat{\mathcal{M}}^m$ were tighter than those corres-

[17] 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.

[18] 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

ponding 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.[19] 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 yet, simultaneously, a remarkable amount of multimodality, 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.

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 densities differences are statistically significant. Since the analysis considered above is based on comparing those 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 the testable hypotheses are more, we have restricted the analysis to the more relevant ones. ****poner tabla descriptora de las hipótesis***** 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.

countries which joined the EU at different points in time, we consider it occurred sufficiently ago as to assume financial systems are not going to integrate further.

19 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.

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 considering jointly different European countries. Our study makes a little breakthrough by encompassing virtually all European Union banking systems—all excepting Greece and the countries adhering to the EU by 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 whether productivity in 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 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 due to 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, out of the only two studies devoted to analyze the productivity growth at the international level, none of them used bootstrapping techniques so as to solve the problem of the 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 among the two subperiods in which the sample was split (1995–1998 and 1998-2001). This productivity growth has involved simultaneously technical progress and efficiency losses. The improvement in "best practice" (technical progress) has occurred both in 1995–1998 and 1998–2001, resulting in a +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. Contrary to most of these studies, in which nonparametric techniques are used to measure efficiency or productivity, yet parametric techniques are considered to find out their determinants—whose remarkable flaws 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 despite of their different nationalities.

A. Summary of bootstrap results, country specific

This Appendix A 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.

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:

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

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, 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:

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

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 have 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:

$$I = I\big(f(x), g(x)\big) = \int_x \big(f(x) - g(x)\big)^2 dx = \int_x \big(f^2(x) + g^2(x) - 2f(x)g(x)\big)dx$$
$$= \int_x \big(f(x)dF(x) + g(x)dG(x) - 2g(x)dF(x)\big) \quad (19)$$

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:

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

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:

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

where

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

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).

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Table 1: Literature review

Authors	Indicators[b]	Approach[a]				Countries	Period	International	Productivity	Bootstrap
		DEA	SFA	DFA	Other					
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 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	
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 (2003)	CE	DEA				9 European countries	1992–1998	YES		
Pastor and Serrano (2005)	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				USA	1980–1993		YES	YES
Williams (2004)	CE, PE		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.

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.

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

	Changes in efficiency (EC)			Changes in technology (TC)			Changes in productivity (TFP)		
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] $EC \times TC = TFP$.

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

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

Table 6: Changes in productivity (TFP), 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] $EC \times TC = TFP$.
(*), (**): significant differences from unity at 10% and 5%, respectively. A number < 1 indicates decline; a number > 1 indicates growth.

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									
	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									
	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		

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

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

Changes in efficiency									
	1995/98			1998/01			1995/01		
	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									
	1995/98			1998/01			1995/01		
	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									
	1995/98			1998/01			1995/01		
	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

Changes in efficiency									
	1995/98			1998/01			1995/01		
	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									
	1995/98			1998/01			1995/01		
	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									
	1995/98			1998/01			1995/01		
	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

Changes in efficiency									
	1995/98			1998/01			1995/01		
	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

Changes in efficiency									
	1995/98			1998/01			1995/01		
	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

Changes in efficiency									
	1995/98			1998/01			1995/01		
	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

Changes in efficiency									
	1995/98			1998/01			1995/01		
	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

	1995/98			1998/01			1995/01		
Changes in efficiency									
	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									
	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									
	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

	1995/98			1998/01			1995/01		
Changes in efficiency									
	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									
	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									
	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

	1995/98			1998/01			1995/01		
Changes in efficiency									
	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									
	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									
	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			9		

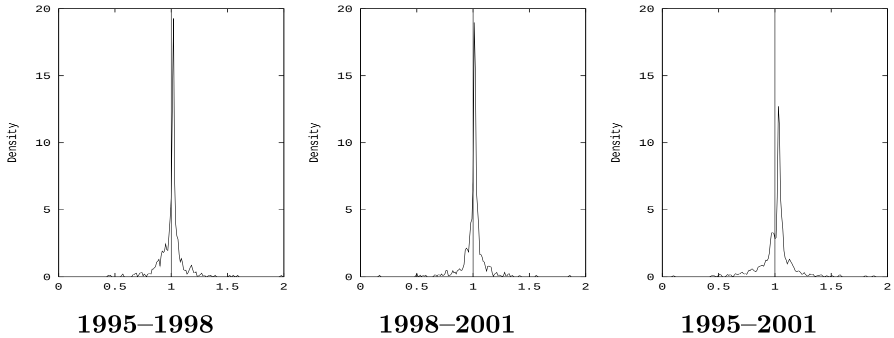
Table 21: Summary of bootstrap results for changes in efficiency, technology, and productivity, Sweden

Changes in efficiency									
	1995/98			1998/01			1995/01		
	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									
	1995/98			1998/01			1995/01		
	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									
	1995/98			1998/01			1995/01		
	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		

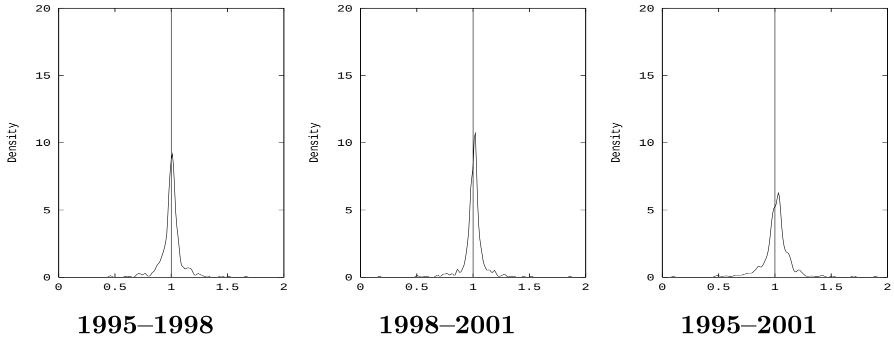
Table 22: Summary of bootstrap results for changes in efficiency, technology, and productivity, United Kingdom

Changes in efficiency									
	1995/98			1998/01			1995/01		
	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									
	1995/98			1998/01			1995/01		
	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									
	1995/98			1998/01			1995/01		
	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		

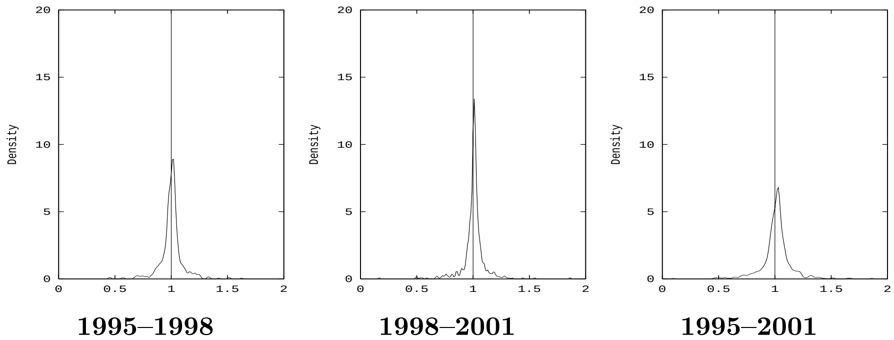
Figure 1: Productivity growth in European banking, densities



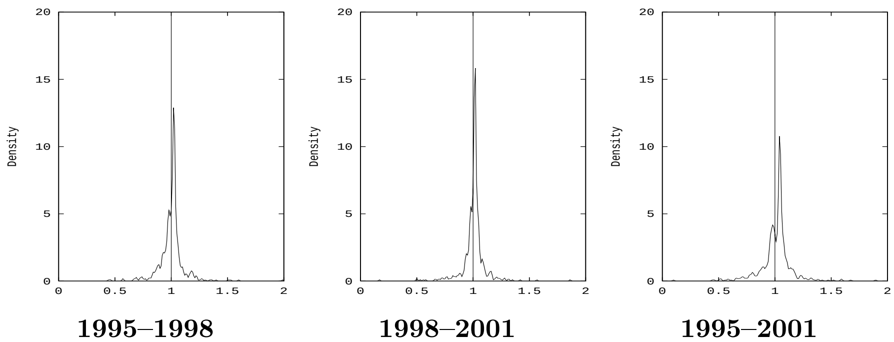
(a) EU14-conditioned



(b) Country-conditioned



(c) Economic neighbor-conditioned



(d) Time of membership-conditioned