Too much EMU? An investigation of technology gaps.

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Abstract

Although European Single Market (ESM) has been widely perceived as a model for regional integration, there continues to be considerable debate about the impact of this integration on the EU regions. Studies in this field have mainly investigated the convergence-divergence issue, while the effect of ESM on regional performance has attracted few empirical studies. The non-parametric metafrontier framework used in this study, as a first stage of analysis, is exploited to account for the heterogeneity between the Italian regions in the whole period and in two distinct time periods before and after EMU implementation. In a second stage, using a partial least squares model, the technology gaps estimated for each period have been regressed, investigating possible factors that may have affected regional performance. Our findings reveal a significant improvement for the Italian regions since ESM implementation, a paradoxically unchanged behavior for efficiency performance in the Centre-North regions, and clear identification of specifically which regions performed better in terms of the technology gap. The inclusion of variables related to regional trade performance in the model indicates that trade balance is of major importance.

Key words: Regional performance, Metafrontier, Technology gap, Partial least squares, ESM, EMU

1 Introduction and motivation

In recent research on regional efficiency, little attention has been given to the issue of the regional degree of openness. Economic theory has analyzed in-depth the role of the degree of economy's openness and its effects on growth. For the classical economic theory time and space dimensions are almost ignored. The classical model implicitly assumes a world made by a homogeneous area, where transportation costs are null and there are no economies of scale. In a world like this, the economic activities in equilibrium should be evenly distributed in geographical terms. On the contrary, in the real world, productive resources, as well as productive activities, population and economic wealth, are unequally distributed among and within countries and regions. In the 1950s and '60s, economic theories were questioning the economic determinants of development, that is, the mechanisms that allow a system to grow and reach certain levels in production, lower rates of unemployment and higher levels of wealth. Under these assumptions, the Keynesian view focused on the demand side, where the local effect of interdependence mechanisms in the production and consumption produces increased income and employment in areas not previously related. Demand is therefore an engine for development. This approach concerns the short run, as it implicitly assumes a competitive production which may be valid only for a short period. In the long run, the local system remains competitive only if it is able to maintain or expand its position in the world market (thus it shows the importance of the role of innovation to foster the growth of total factor productivity). On the other hand, the neoclassical theory of economic growth indicates the relations between labor, capital, levels of investment and economic output. In these models, a central role is ascribed to technological progress, which is useful to reduce production costs and to introduce newer goods.

Despite these different theoretical approaches, Dollar and Kraay (2004) assert that "Openness to international trade accelerates development: this is one of the most widely held beliefs in the economics profession, one of the few things on which Nobel prize winners of both the left and the right agree". There is, however, a non-orthodox view based on Thirlwall's works (1979, 2011) according to which regional trade agreements reduce growth and investment, but generalize trade liberalization in the form of unilateral tariff reductions and thus improve growth performance. This debate, albeit extremely important, lies beyond the scope of this work since we consider EMU adoption as the widest degree of openness of the Italian regions and we are interested in comparing the efficiency of the regional economies in light of this new degree of openness. Hence, as proposed by Krieger-Boden (2002) it is interesting to analyze the potential effect of EMU on the income of European regions. Krieger-Boden started from a reduction of transaction costs that could lead to an increase in trade links and a change in regional centrality[64]. The former can lead to industrial regional specialization, while the latter efficiency and growth of regions. The final step of this process could be an increase in regional income. Moreover, as shown by Martin (2001), it is important to know how quickly regions adjust to the EMU process. This is difficult due to the absence of a concrete theoretical background. Finally, the regional economic direction is not certain since the market process tends to generate persistence and leads to convergence-divergence.

In so doing, our approach is consistent with that presented by Winters (2004) who argues that "while there are serious methodological challenges and disagreements about the strength of the evidence, the most plausible conclusion is that liberalization generally induces a temporary (but possibly long-lived) increase in growth. A major component of this is an increase in productivity".

The last statement, in particular, is strictly related to the methodology we apply in this work. In general, theoretical studies on regional productive performance have assumed that within a country, efficiency levels are measured in relation to a frontier. However, the estimated frontiers for different regions are quite unlikely to be so similar as to make the use of a single frontier possible. Empirical studies tend to reject the null hypothesis of constancy of the production frontier across different regions, denoting significant differences due to the available stock of physical, human and financial capital; economic infrastructure; the allocation of resources and all other characteristics of the physical, social and economic environment in which production takes place [52] [37]. Therefore, precisely in these cases it is crucial to construct one metafrontier for comparison of performance of different regions. The advantages of the metafrontier are that it allows for the comparison of different technologies, separation of technological measures from efficiency and it is also parsimonious in terms of data requirements.

The objective of this study is to determine empirically the productive performance of Italian regional growth over the period 1993-2011, taking into account the highest degree of openness of the regions at the start of European Single Market (ESM). We also check for the effect of the launch of the European Monetary Union (EMU). Hence, the metafrontier framework is used to measure and compare the productive performance of the Italian regions under different technologies before and after EMU. Moreover, by constructing two macro-region frontiers it is possible to check the productive performance of regions that operate in more "homogeneous" areas. In doing so, a set of specific macroeconomic variables like regional trade balance, imports and exports (within the EMU area and with the rest of the world), are implemented.

The paper contributes to the literature in several ways: first, it investigates the effect of ESM on productive performance in the Italian regions; secondly, the adoption of a bootstrap DEA approach provides technical efficiency and technological gap scores with a high statistical precision; thirdly, it attempts to explain technology gaps, before and after EMU adoption, from the econometric point of view, focusing on factors that shape degrees of openness as an exogenous set of variables.

There has been no study, to the best of our knowledge, commissioned to investigate the technological gap in productivity performance related to the degree of openness for the Italian regions. In addition, this study extends the period of study up to the year 2011 as compared to the previous studies, thus taking into account the effect of the latest financial and economic crisis and its effects on Italian regional productive performance.

The analyses of regional productive performance within the same national framework are important and challenging at the same time. From a policy point of view, it is of great interest to distinguish the regional differences in mean efficiency levels and to determine whether the regions share some characteristics. Centralized fiscal policy, and moreover European monetary policy, can have different impacts on different groups of regions.

The rest of the paper is organized as follows: section 2 presents the empirical literature review on this topic. Section 3 details the meanings of group and metafrontiers as well as technology gap ratios. Section 4 presents the empirical model to be used in this study. Section 5 describes the empirical results. Finally, conclusions and policy implications are detailed in section 6.

2 Literature Review

To our knowledge, there has been no publication that applies metafrontier to assess the impact of trade on regional economic performance, which still remains a controversial topic. In this section, we therefore present a brief, non-exhaustive overview of some of the work that has been done on comparing regional growth; trade openness and regional growth; some relevant papers on the methodologies applied in this study.

In the literature, several channels are discussed through which trade can affect economic growth. Grossman and Helpman, (1991), and Sala-i-Martin and Barro (1997), assert that trade is a vehicle through which technological innovations as well as knowledge are spread among different economic areas. Moreover, higher degrees of openness, as pointed out by Vickers and Yarrow (1991) and Wacziarg (2001), also increase competition in the regional/local market, which in turn increases productive efficiency and economic growth.

The experience of the last three decades seems to strengthen the position in favor of free trade. Since 1982, the size of the trade sector has roughly doubled. Although the protectionist position continues to benefit from extensive credibility among political leaders and in the media, it receives little support among economists. Several surveys have pointed out that more than 85 percent of all economists believe that free trade improves economic prosperity. For example, Rodriguez and Rodrik (2000) have highlighted some concerns about the validity of these results since in some cases the findings were affected by the difficulty of measuring openness and the statistically sensitive specifications.

In general, previous empirical studies tend to give contradictory results. Some of them, like Bleaney (1999) and Ahmed (2000), show that the countries which become more open have improved their export performance. On the other hand, other studies [11] [24]have found little evidence of this relationship.

Another remarkable characteristic of the analysis is whether the regional growth level and trade balance are affected by liberalization. The timing of trade liberalization within a country could also affect this relationship. If closer integration improves the efficiency of different combinations of factors, this process is likely to result in even more investment. While all this is in place, countries can experience an effect of growth in the medium term. Moreover, if this investment leads to a rapid accumulation of technical progress and human capital, then long-term growth rates can also be improved. In fact, more importance is now given to the impact of regional integration on production via the effect on trade. Following the European Single market's experience and consequently its Monetary Union, there is now greater consciousness of the importance of barriers, which can increase transaction costs in reducing trade, and of the importance to eliminate them. The economic theory as well as empirical evidence have shown that economies that are more export- oriented have higher level of productivity and also tend to grow faster. This allows us to state that income growth depends primarily on the ability of a country to increase its productivity. This productivity, both at the national and regional level, is also driven by the degree of openness to trade which is the driving force of productivity. In addition, it allows a more efficient allocation of resources and offers more opportunities to make the most of the economies of scale. This process exposes the national or regional economies to increasing competitive pressures from greater incentives for investment and pushing them to new levels of innovation and the use of new technologies. Taken together, these factors mean that openness to trade can play an important role in increasing the long-term sustainable rate of productivity growth in the regional economy.

Hence, does openness promote economic growth and boosts productive performance? There is significant divergence on this particular question: some economists assert that increased competition from foreign countries may discourage innovations of domestic producers by lowering their expected profits. Lucas (1988), Grossman and Helpman (1991), Young (1991), and Rivera-Batiz and Xie (1993) show that economic integration, while being able to raise the worldwide growth rate, could adversely affect individual countries even if trading partners have considerably different technologies and endowments [82].

In the efficiency literature there are two broad methods used for arriving at measures of relative efficiency [13]. Data envelopment analysis (DEA) as a non-parametric technique and stochastic frontier analysis (SFA) as a parametric approach that assumes a functional form for the benchmark frontier have been mostly used in assessing the performance of many decision making units (DMUs). However, should a typical DMU face different production possibilities? The recently analytical metafrontier approach [4][57][3] inspired by the work of Hayami and Rutan (1970,1971) and developed by O'Donnell et al. (2008) provides an alternative methodological approach to the two DEA or SFA approaches, to evaluate and compare the efficiency of DMUs that belong to different groups. Moreover, the introduction of a metatechnology ratio or technology gap indicates the improvement made by its DMU in order to use the best practice technology, as has been defined by the technology of all DMUs participating in the sample.

The present study extends analogous research on metafrontiers to a temporal framework linking the measurement of regional efficiency growth over time for 20 Italian regions. In this context, it would be of some interest to examine how the different Italian regions perform with respect to the national technological frontier. It is also worth noting that all the mentioned studies derived their decompositions under the assumption that all the countries/regions in a group operated under a common technology. This study extends previous research by considering two groups of Italian regions working under different technologies (North-Center and South), thus relaxing the common technology assumption, as well as explicitly accounting for temporal effects, which measures productivity and efficiency changes over the period 1993-2011.

3 Methodology

3.1 Definitions and notation

Let us assume that a region employs a vector of inputs $x \in R_+^N$ to produce a vector of output $y \in R_+^M$. Also let $N = \{1, 2, ..., N\}$ and $M = \{1, 2, ..., M\}$ be the input and output sets containing non-negative real values formally stated as $x \in R_+^n$ and $y \in R_+^m$, respectively. The production possibility set is given as $T(x) = \{(y, b) : x \text{ can produce } (y, b)\}$ with the output set defined as $P(x) = \{y \in R_+^M : (x, y) \in T\}$.The output-oriented efficiency of a region with respect to technology T can then be measured with respect to the output set through the direct output distance function, defined as $D_O = \inf\{\delta > 0 : x/\delta \in P(x)\}$. The efficiency score for a given point (x, y) is given as:

$$\widehat{TE(x,y)} \equiv \widehat{\theta(x,y)} = \max\{\theta \mid \theta y \leq \sum_{i=1}^{N} \gamma_i y_i ; x \geq \sum_{i=1}^{N} \gamma_i x_i \text{ for } \gamma_i \tag{1}$$
$$\text{such that } \sum_{i=1}^{N} \gamma_i = 1; \gamma_i \geq 0, i = 1, 2, ..., N$$

In the case where multiple technologies become applicable, each region is considered as operating under exactly one of those. Thus, given k distinct technologies $T^1, T^2, ..., T^k$ the metatechnology set, denoted as T^M, is the smallest convex set containing all input–output feasible combinations (e.g. see [52]). Formally, $T^M = conv.hull\ (T^1 T^2, ..., T^k)$ or

$$T^M = \{(x, y) : x \geq 0, y \geq 0,\ x \text{ can}$$
$$\text{produce } y \text{ in at least one of } T^1, T^2, ..., T^k\}.$$

The output set $P^M(x)$ associated with the metatechnology is defined as for a single technology, while the corresponding efficiency of a region with respect to the metafrontier or, in other words, the homogeneous boundary for all heterogeneous regions can be measured by the output-oriented metatechnical efficiency score (MTE) and it is easy to obtain by solving an analogous LP problem as in (1).

The metafrontier analysis is an approach that allows the comparison of different technologies [4]. The characteristic of the metafrontier as an envelope of all the respective frontiers offers the opportunity to account for all the possible existing heterogeneity between the DMUs participating in a dataset [57] [2]. Put another way, the MF paves the way to estimate the technology differentials between a specific frontier and its respective metafrontier [4]. To illustrate our definitions graphically, consider the case in which there exist two separate technologies T^1, T^2 that correspond to group frontiers F_1, F_2 (denoted here as *South* and *North - Center*) respectively as shown in Fig.1.

In this context, the metafrontier MF which corresponds to metatechnology T^M is defined as the overall frontier that includes all the Italian regions such that no point of these frontiers can lie above points of the metafrontier[4]. Consider an Italian region denoted by point A using an input vector in order to produce an output in Fig.1. This region has access to its technological set T^1, as represented by the efficiency South frontier $F_1$and at the same time to the technology common to all regions, the *Italian metatechnology* corresponding to metafrontier MF after.

Thus we can define the distance functions with respect to the South frontier and the metafrontier MF after in order to calculate the technology gap ratio [4] or the reciprocal relationship of metatechnology ratio

[52]. Following O'Donell et al. (2008) the metatechnology ratio is defined as

$$MTR(x, y) = \frac{MTE(x, y)}{TE(x, y)} = \frac{\left(\frac{OA}{OB}\right)}{\left(\frac{OA}{OC}\right)} \tag{2}$$

and identifies technology differentials among the Italian regions due to production structures[1] . Estimation of the technology gap, hence the distance between the individual frontier and the metafrontier (distance CB in Fig.1), can be defined as

$$MTG(x, y) = 1 - MTR(x, y) \tag{3}$$

3.2 Bootstrapping in DEA

The bootstrap method in efficiency analysis was introduced by Simar and Wilson (1998; 1999; 2000) and refers to the concept that the bootstrap distribution will mimic the original distribution of the parameter estimates of the efficiency scores of a given dataset of (x, y). It was built upon the idea of overcoming the major weaknesses of DEA that does not suffice to establish stochastic elements in the production process. Therefore, the statistical noise may distort any kind of efficiency ranking. Statistical noise may capture, amongst other things, single DMU idiosyncrasies, measurement errors, and technology heterogeneity in the sense that a group of DMUs is benchmarked against one that exhibits significantly different production and behavioral characteristics.

Hence, the bootstrap procedure enriches the toolbox of the efficiency literature since it allows for statistical inference and accordingly hypothesis testing along with the construction of confidence intervals and bias correction for the DEA estimates i.e [71]. This is achieved by employing Monte Carlo approximation as a consistent estimator of the true, yet unknown, data generating process, the DGP. Briefly, let us assume a data generating process DGP, P that generates random samples $X = \{(x_i, y_i), i = 1, 2, ..., n\}$ and suppose we aspire to estimate the efficiency scores given of the DMUs participating in this sample. However, as the DGP, P is unknown, the bootstrap procedure can be employed to determine the $\widehat{DGP, P}$ as a consistent estimator of P .

The efficiency estimates by using the $\widehat{DGP, P}$ can be considered as a "new" population from which we can draw a new dataset $X = \{(x_i, y_i), i = 1, 2, ..., n\}$. The specific "pseudo-sample" can now be used, to define $\widehat{\theta^*(x, y)}$ with respect to $\widehat{\theta(x, y)}$ at the specific point (x, y). Note that it may be difficult to compute the true distribution $\widehat{\theta^*(x, y)}$ of resulting from a sample $X^* = \{(x_i^*, y_i^*), i = 1, 2, ..., n\}$ drawn from $\widehat{P}$ and thus Monte Carlo approximation can be employed to construct the sampling distribution of $\widehat{\theta(x, y)}$.

With B denoting the number of bootstrap replications it becomes evident that the generation of B pseudo-samples as much as that of the pseudo-estimates of the efficiency scores is not impossible to achieve. However, this bootstrap procedure (called at this stage "naive") yields inconsistent estimates of θ scores (Simar and Wilson, 1998) and development of a smoothed procedure to overcome this difficulty is required .

[1] The output-oriented technical efficiency with respect to the South frontier is calculated as OA/OB while the corresponding distance with respect to the metafrontier is defined as OA/OC

Following closely Simar and Wilson's procedure we are able to estimate the bias for the original DEA estimator as:

$$\widehat{bias_i} = \frac{1}{B}\sum_{b=1}^{K}\theta^*_{i,B}\widehat{(x,y)} - \theta_i\widehat{(x,y)} \tag{4}$$

where B represents the number of bootstrap replications. Consequently , a bias corrected estimator of $\theta^*_{i,B}\widehat{(x,y)}$, is given as follows:

$$\widehat{bias_i} = \theta^*_{i,B}\widehat{(x,y)} = 2\theta_{iB}\widehat{(x,y)} - \frac{1}{B}\sum_{b=1}^{K}\theta^*_{i,B}\widehat{(x,y)} \tag{5}$$

3.3 The Partial Least Squares Methodology

We estimate the relationship between different regional aspects of openness and technology gap using a Partial Least Squares (PLS) technique [81] a variance-based structural equation modelling (SEM) approach. This model was considered the most suitable since it covers, in depth, the research objective, the explanatory nature of the specific relationship and the latent nature of the participating variables. Moreover, the PLS technique avoids inadmissible solutions and factor indeterminacy [23, 10]. and accounts for the presence of formative and reflective constructs [7]. Moreover, using small samples [55] [27] and samples with no strict distribution [27] is well grounded in statistical theory [9]. Hence, PLS regression is evidently associated to multiple factor analysis. This relationship is analyzed in detail by Pages and Tenenhaus (2001). The main originality of PLS regression is to preserve the asymmetry of the relationship between predictors and dependent variables, whereas other techniques treat them symmetrically. It also tends to eliminate multicollinearity in the set of explanatory variables X of a regression model reducing them. The PLS method first standardizes all series. Then a simple recursive computing scheme yields a sequence of underlying factors. An analytical description of the nature, reasons to adopt and presentation of partial least squares methodology can be found in Cheety et al. (2014), Marcoulides and Saunders (2006), Marcoulides (2003) and Lohmoller (1989).

3.3.1 Specification of the model

Being consistent with the motivation and scope of this paper we account for the impact of Italian regional openness on the technology gap before and after EMU adoption using a partial least squares model consists of three component models referred to as i) the inner (or structural), ii) the outer (or measurement) and finally iii) the weight model [7]. Mathematically, the PLS model can be represented as follows, stating the relations between the latent variables. Thus,

$$\eta = B\eta + \Gamma\xi + \zeta \tag{6}$$

where η, ξ are the vectors of endogenous and exogenous latent factors respectively; B and Γ denote the matrix of coefficients of their relationships and ζ the vector of error term satisfying $E(\zeta \mid \xi) = 0^2$.On the other hand, the measurement model that specifies the relationship between the latent variables is presented as follows:

$$x = \lambda_x \xi + \varepsilon_x \tag{7}$$

$$x = \lambda_y \eta + \varepsilon_y \tag{8}$$

where x, y manifest the indicators that fulfil the predictor specification[3] [80][81] and can be split into blocks related to latent variable; λ_x,λ_y are the loading and, ε_x,ε_y are the errors related to different latent variables and are uncorrelated[35]. Finally, the weight relations defining scores of the latent variables as weight means of the manifest variables are presented as:

$$\eta = w_\eta y \tag{9}$$

$$\xi = w_\xi y \tag{10}$$

4 Data and Variables Definition

In most empirical studies of the metafrontiers, grouping of countries/regions are implicit in the problem under consideration. However, since there are no a priori theoretical prescriptions, when estimating frontiers, on how countries/regions should be allocated to groups, we consider the historical-geographical Italian regions criteria [41]. The uniqueness of the Italian case is found in the fact that the three types of dualism analysed in the literature (territorial, industry/sector and dualism in the labour market) tend to coexist, creating a clear separation between the North-Center and South of the country [20].

Moreover, recent studies have studied the importance of the dualistic nature of the Italian economy in terms of macroeconomic variables like unemployment, income growth, public finance and technological gap. Among the latter studies, Evangelista et al., 2002 and Iammarino et al., 2004, showed that the gap in technological endowment and capacity for innovation has been one of the main factors behind the divergence between Italian regions.

The data used to estimate the DEA in this study consist of two inputs and one output. The dataset comprises annual observations and covers all twenty Italian administrative regions and the full sample period under investigation is 1993-2011. Most of the data were obtained from different databases published by ISTAT (National Institute of Statistics). In order to examine our second hypothesis concerning the efficiency of adopting the euro we created two different periods (1993-1999 and 2000-2011). At the same time we averaged all constructed variables over these periods in order to avoid the well-recorded fluctuations of data

[2] Implying that $E(\eta \mid \xi) = (I - B)^{-1}\Gamma\xi = \Pi\xi$
[3] $E(y \mid \eta) = \lambda_y \eta$, $E(x \mid \xi) = \lambda_x \xi$

due to business cycles [70].[4]

The output factor data (Y) used is the gross regional product (ISTAT source)[21][48]. As input factors, the following variables are utilized: labor input data (L) (level of employment) drawn from the national labor force survey and the region's gross fixed capital formation in millions of euro were taken from ISTAT (year 2011 is based on forecasts made by Prometeo-Bank of Italy)[48][49] as a proxy for the construction of capital (K). However, in order to construct the region's capital we follow the perpetual inventory method (PIM) which can be expressed as

$$K_{it} = (1 - \beta_i)K_{it-1} + I_{it}$$

where $K_{it}$is the capital stock of region i in year t, I_{it} is the investment in region i in time t and β is the rate of depreciation.

Two additional variables are used to describe the degree of openess and are able to capture possible factors affecting technology gaps for the participating regions. As such, we used imports and exports towards the European Union (EU25 countries) and toward the rest of the world, respectively [5].

The 20 regions are also divided into two macro areas, namely North-Center and South. The former is made up of 12 regions, while the latter comprises 8 regions[6]. The descriptive statistics for input and output variables are shown in Table 1.

5 Empirical Results and Discussion

As discussed in Section 1, our study examines efficiency mataefficiency scores and technology gaps in the Italian regions at the start of the European Single Market and also before and after EMU adoption, thus implying the existence of two or more distinct technology sets. In this section, we present our empirical findings of a two-stage analysis. First, we derive and compare technical efficiency scores for Italian regions between the periods examined, and secondly, we investigate a number of factors that are likely to affect their technology gaps in the time periods in question.

5.1 Results with respect to region-specific frontiers

DEA bootstrap, on average, results for the 1993-2011 are presented in table 2. The North-Center frontier, in average terms, the bootstrap efficiency scores estimated is 0.833 while the corrensponding score for the

[4]Italy has twenty administrative regions; the economic regions reflect the different economic structures across the country. They are defined as North-Center (LIG-Liguria, PIE- Piemonte, VDA- Valle d'Aosta, LOM- Lombardia, FVG- Friuli Venezia Giulia, TAA- Trentino Alto Adige, VEN- Veneto, EMR-Emilia Romagna, LAZ-Lazio, MAR- Marche, TOS-Toscana, UMB-Umbria), South (ABR-Abruzzo, BAS- Basilicata, CAL-Calabria, CAM-Campania, MOL- Molise, PUG-Puglia, SAR- Sardegna, SIC-Sicilia). In the remainder of the text, the terms economic regions' and macro-regions/areas' will be used according to this classification.

[5]It should be noted that we also considered a number of additional variables in the context of the previous two categories (e.g R&D expenditures, populations density, trade balance, public expenditures, e.t.c) however their inclusion was not found to improve the econometric performance of our model

[6]For the south they are: Abruzzo, Basilicata, Campania, Calabria, Molise, Puglia, Sardina and Sicily. All the other regions belong to the North-Center group.

South specific frontier seems on average is 0.938.

The results of the bootstrap DEA estimations for the two sub-periods with respect to the region-specific frontier are shown in Table 3.The technical efficiency scores estimated for the South-specific frontier do not exhibit great variations among the regions prior to EMU adoption. Similar results are obtained for the second period (after EMU adoption). However, in comparing the technical efficiency scores between the same regions in the two periods, the upward shift of the macroarea specific frontier is evident (from 0.915 to 0.953). It is also worth noting that the ranking of each region in the two periods has changed, implying a re-location of some in terms of technical efficiency along the new frontier.

Again, technical efficiency scores estimated for the North-Center specific frontier exhibit quite a substantial variation among the regions before and after EMU adoption. Moreover, the results show a clear downward shift of the North-Center frontier while the ranking of each region in the two periods has not changed, implying, in terms of technical efficiency, a relative stable position of each region in both periods (see figure 2 for the North-Center and figure 3 for the South). The results show a picture that is consistent with the previous empirical analysis prior to EMU, that is, the North-Center that was more technically efficient, but they also show an unexpected economic performance of the South after EMU adoption. In particular, it is well known that regional disparities, especially the gap between North and South, remain the unsolved problem of the country. It is also well known that the theory of monetary unions shows that the consequences of negative external events are never symmetrical, affecting the weak regions more severely than the dynamic ones.

It cannot be ignored, however, that paradoxical as it may seem, the process of European monetary unification have produced even a positive impact on the economy of the South. In fact, as the localized spillovers theory predict, a number of companies in the North-Center have relocated stages of production to other countries, where labor costs are lower and other factors like legislation and environmental protection are less stringent [74].Nevertheless, this extreme measure of reorganization at a great distance remains the domain of companies of sufficient size and financial capacity to meet the necessary effort. The smaller companies, also under pressure from the competition, were unable to move to distant countries, and thus they outsourced part of their activities to regions in the south. The result was a growing number of small businesses, many of which work directly or indirectly on the basis of orders from North-Center [63].

This evolution of the southern industrial sector gives rise to very diverse opinions. For instance, the presence of smaller firms, as the result of spontaneous local initiative, could eventually lead to reproducing in the South the positive experience of the industrial districts that have made the fortune of many regions in central Italy [76]. It should be also noted that many of the smaller companies in the South live mostly as undeclared businesses, dealing with irregular work. However, as an example of far more promising development, it is worth mentioning the presence of a small but significant number of new high-tech companies in the IT sector [16].

5.2 Results with respect to metafrontier

The average results of the DEA, bootstrap DEA, technology gaps and metatechnology ratios for the period 1993-2011 are presented in table 4. From this table and in average terms, TAA, LAZ and EMR regions are the best performers in contrast to CAM, CAL and ABR regions. Furthermore, an average a relative high score (0.86) of metatechnology ratio exists but a closer inspection reveals the formation of two different groups (North-Center and South). For almost half of the participated regions no technology differentials can be detected due to the Italian production frontier while for the other half, technological differentials exists in a significant way. As it can be seen, regions that belong in the South are far away, on average term, from the Italian metafrontier due to regulations and policies, the structure and operation of their markets[52], cultural profiles and legal and institutional frameworks [28], available resource endowments, economic infrastructure, and other characteristics of the physical, social and economic environment [38] [37] [39]. The specific results reveal a distinct and differential behavior of Italian regions and justify our categoriazation in North-Center and South .

The results of the bootstrap DEA estimations, technology gaps and metatechnology ratios for both periods are shown in table 5. The technical efficiency scores estimated for all the regions exhibit a clear shift upward when we move from before to after the launch of the EMU. Figure 4 shows the results obtained in table 5 comparing the metafrontier ratio (MTR) before and after.

From the empirical evidence shown in figure 4, a strong "macro-area stamp" can be observed here. The results reflect a significant spatial autocorrelation. The consequence of this "macro-area stamp" is that regions belonging to the same macro area can be clustered in some specific areas of the plot. For instance, Southern regions are clustered on the left because they experienced a clearly below–average MTR after EMU. In particular, regions like Puglia, Campania and Basilicata have been worse off since they had an MTR above the average in the first period. The Center-North regions are clustered on the right side of the graph, all above the average. At the bottom right the graph shows the cluster of regions that are better off compared to the MTR of the previous period, and all are above average. Finally, the most dynamic regions are clustered at the top right side. The linking criterion within this latest cluster seems to be the ability of the regions belonging to it to face the pre and post EMU phase, independently of the economic behavior of the area where the specific region was located (North-East, North-West or Center). Figure 5 graphically summarizes the shifts of each region-specific frontier and the metafrontier in the two periods.

It is worth noting that, in contrast to the results obtained with the regional specific frontiers, the ranking and the relative position of each region in the two periods did not change, implying a stable allocation of them in terms of technical efficiency along the new frontier (tables 6 and 7).

5.3 Econometric strategy and factor affecting the regional technology gap: PLS analysis

Data used in this study allow us to estimate the following structural model that consists of two exogenous variables namely $OPEN_{25}$,$OPEN_W$ and one endogenous TG. The selection of the outer model (reflective or formative) is subject to theoretical reasoning [17] but also depends on sample size satisfying a "rule of thumb"[45]. The research model is depicted in Fig.5 in which the region's technology gap is modeled as a formative construct while imports and exports are the reflective indicators. Thus, the inner structure can be described as:

$$TG = \gamma_1 OPEN_{25} + \gamma_2 OPEN_W + \zeta \tag{11}$$

where the manifest variables are denoted by $x = (IMP_{25}, EXP_{25}, IMP_W, EXP_w)$ for the $OPEN_{25}$,$OPEN_W$. The formative measurement model for $OPEN_{25}$,$OPEN_W$ is given as:

$$OPEN_{25} = IMP_{25}\pi_1 + EXP_{25}\pi_2 + \delta_1 \tag{12}$$

$$OPEN_W = IMP_W\pi_3 + EXP_W\pi_4 + \delta_2 \tag{13}$$

while there is no reflective measurement model for TG with π the coefficients and δ the random errors. The imports and exports among the EU25 countries (EX_{25} and IMP_{25}) and the imports and exports with the rest of the world (EX_W and IMP_W) are used to estimate the relationship between regional different aspects of openness and technology gap for all the period and before and after the EMU launch. The results of the structural model (see Fig.6) are presented in Table 9. Furthermore, we run the model using a bootstrap procedure, resampling 500 times. As can been noted the R^2 of endogenous construct for all the models are very high. Moreover we also computed the goodness of fit (GoF) [69], an overall quality measure of the model.

The software used was a PLS path modelling package in R (Sanchez[7], 2013). At this point we have to note that the criteria of assessing the two different types of constructs are different and thus we report them separately. In Table 8 we present item weights, loadings and communalitites (AVE). All item loadings, for both models, are significantly greater than 0.7, indicating convergent validitiy at the indicator level while AVE values are greater than 0.5, suggesting convergent validity at the construct level. Moreover, Cronbach's alpha, a coefficient that evaluates how well a block of indicators measure their corresponding latent construct, appears to have values larger than 0.7 (0.908-0.781, 0.972-0.971 and 0.65-0.976 for $OPEN_{25}$, $OPEN_W$ for all, pre and post EMU, correspondingly[8]).

Table 9 shows the importance of international trade in reducing region's technology gap, over the period 1993-2011, when we consider the widest degree of openness of the regions as coinciding with the start of the European Single Market process (1993). From the PLS we extrapolated two latent variables called $OPEN_{25}$, $OPEN_W$, respectively. Each represents the main underlying factor able to explain the optimal determinants for predicting our dependent variable (technology gap).

When the all sample is considered, the results show a link between the degree of openness of the Italian regions and tecnology gap(-0.707 and -0.438, respectively). Furthermore, the results for the pre-EMU period

[7] http://www.gastonsanchez.com/PLS_Path_Modeling_with_R.pdf

[8] Dillon-Goldstein's rho, a metric used to access the unidimensionality of a reflective block, again reveals values greater than 0.7.

reveal a clear link between the degree of openness of the Italian region. Indeed, both coefficients are negative and significant with a stronger effect of the openness towards the 25 European countries (-1.127) and a cumulative impact on technology gap of about -1.5. To summarize, our main results from the PLS are negative and significant relationship between degree of openness and the technology gap. In particular, we found that within the first period the magnitude of the coefficient was stronger for the EU countries than for the rest of the world. These results are in line with the EMU process and the exchange rate control re-established in 1995, three years after the Exchange Rate Mechanism (ERM) crisis. To reinforce this result, it is worth noting that the intra-EU balance of trade was valued on average about 1.7 times higher than the level recorded for exports from the EU-28 to non-member countries (extra-EU trade). The importance of the EU's internal market was underlined by the fact that intra-EU trade of goods was higher than extra-EU trade in each of the EU Member States. Our empirical exercise also confirms for the second sub-period the importance of a wider degree of openness in reducing the technology gap.

However, we obtain different results for the post-EMU period. Openness toward the rest of the world becomes positive but not significant. How can we explain this questionable ambiguity? Among the many explanations that could be found, we think the following two are of particular interest for the specific Italian case.

The first is related to what Pellegrino and Zingales (2014) call the Italian disease that is, the slowdown of Italy's labor productivity growth. Despite the common belief they found that this slowdown was not caused by excessively protective labor regulation but with the small size of the firms that were unable to challenge the Chinese competition after EMU when it became stronger and also by failure to take full advantage of the ITC revolution. The small firm structure was considered at the end of the 1970s and during the 1980s as a strength of the Italian economy because it gave them some levels of flexibility useful to compete at an international level. However, during the 1990s the process of globalization inexorably shifted the focus of economic policy away from nation states and toward the two ends of the two territorial extremes: the regional and urban dimension, on the one hand, and the supranational and international, on the other. In this dynamic of dual polarization toward the global and toward the local a major role is played by new technologies. In investigating the sources of regional technology gap differentials for the Italian regions before and after EMU adoption we discover a different behavior of the "open" variables. The specific finding, for the second period, is in accordance with several studies that support the idea that R&D spending would dramatically increase the innovation performance of the region [6], explains regional disparities in growth rate [47], is positively correlated with the external factor of the regional components and enhances technology transfer through the ability to assimilate and manage knowledge in order to improve innovation performance and competitive advantage (absorptive capacity) [25] and knowledge spillovers[9] which constitutes an important factor in shaping the regional conditions for innovation activities [41].From a theoretical point of view, investing in R&D constitutes a strategic choice [18] for many regions, shaping a sustainable competitive advantage [59] that leads to the so-called "technology push hypothesis[10] [51]. Hence, firms' size, failure to take full advantage

[9] Departing from the seminal works of Cohen and Levinthal (Cohen and Levinthal, 1989; Cohen and Levinthal, 1990) and the widespread consensus on the specific role of 'knowledge' for innovative performance, these concepts have been widely employed in regional studies (Jaffe, Traijtenberg, and Henderson, 1993; Maurseth and Verspagen, 2002; Doring and Schnellenbach, 2006).

[10] Mowery and Rosenberg (1979) claimed that it is technically complicated to distinguish a demand-pull situation from a

of the ITC revolution and lack of R&D investment in worldwide trade can be seen as the main factors that explain the equivocal ambiguity of our results. The second explanation is related to the monetary policy and the exchange rate policy of the Bank of Italy during the 1990s and the ECB afterwards. After the ERM the devaluation of the Italian Lira pushed up the regional exports due to a sort of devaluation, that is, a "beggar-thy-neighbor" type of economic policy toward, in particular, the European countries. Indeed, the previous empirical analysis of small and medium-sized enterprise (SME) activities among regional exporters in Italy show that they tended to be isolated entrepreneurs who relied primarily on their internal innovation. Often, they did not depend on local networks or clusters as recommended by regional economic theory [75]. Several of these companies were small firms which entered world markets with an original niche product and were helped by the low exchange rates prevailing at that period. The beginning of the 2000s were years of weak Euro exchange rate but the pegged value of the Chinese currency and the subsequent financial crisis did not help the regional Italian firms to remodel their competitive structures.

6 Conclusions

The issue of regional performance within the European Union has attracted a great deal of attention in recent years. Given the dynamic transformation of European regions through economic integration, key questions arise concerning their technology capacity, competitiveness their overall performance. There is also considerable interest in, and discussion about, economic integration among EU Member States and the impact of this integration on the countries' regions. Studies in this field mainly investigate the convergence-divergence issue, while empirical studies concerning the effect of EMU on the regions' performance are rare.

All the EMU countries should share a similar interest in improving productivity growth performance at the regional level in order to maintain their competitiveness in the rapidly changing environment of a more competitive worldwide market. Since comparison of productivity among European countries is rare, this current exercise makes an important contribution to the literature.

Productivity growth is known to be one of the key elements of success of economic development. Long term productivity growth accompanied by the dominant role of technical progress sustains the country's economic growth. In general, technical efficiency improvement of some regions must be balanced by technical progress performance.

As the first stage of analysis, our study encompassed two decades and we used the non-parametric metafrontier framework to account for the heterogeneity between the Italian regions for all the sample and in two distinct time periods before and after the EMU implementation . In the second stage, the technology gaps estimating for each period, has been regressed investigating possible factors that may have affected their performance.

Our findings reveal, for all the period, a high performance on average for the South frontier while a lower one for the North-Center frontier. Moreover, comparing the regional technology gaps with respect to the Italian metafrontier, our result justify the existance of North-South paradigm.

technology-push one.

Focusing on the two sub-periods, a clear improvement in terms of technical efficiency appear for the twenty Italian regions after EMU integration; a paradoxically small reduction for the efficiency performance of the Center-North regions holds; a clear identification of all the regions performing better in terms of the technology gap. The breakdown of the time span into two additional periods, before and after adoption of the euro, gave us the opportunity to test different determinants of technology gaps. Furthermore, the use of PLS estimation with the inclusion of latent variables related to the regional degree of openness indicates a clear link between the degree of openness of the Italian regions for all and the pre-EMU period. In particular, we found that within the all and the first period the magnitude of the coefficient was stronger for the EU countries than for the rest of the world. We obtain different results for the post-EMU period. Openness toward the 25 European countries is confirmed to be negative and significant while the openness coefficient of the rest of the world has become positive but not significant. We explain this questionable ambiguity with the regional firms' size, failure to take full advantage of the ITC revolution, lack of R&D investment and the exchange rate policy of the Central Bank. Moreover, the present study points to some interesting directions for further research including the application of this analysis to other countries and/or to the European Union as a whole.

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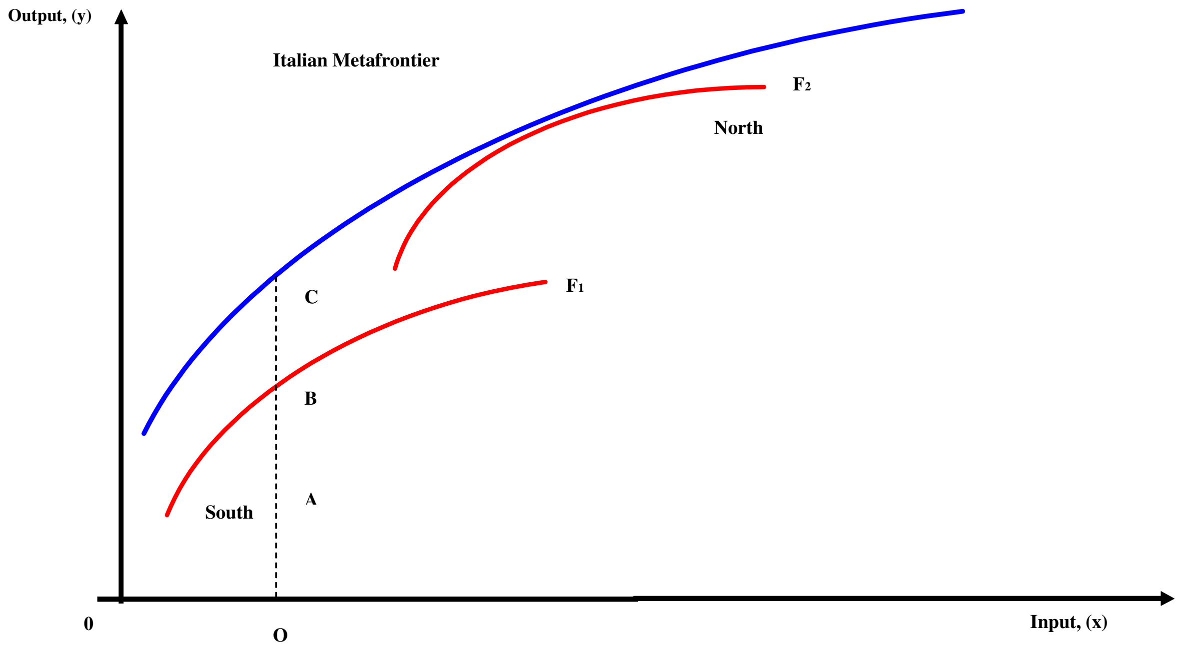

Figure 1: Output-oriented technical efficiency and technology gap.

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7 APPENDIX I

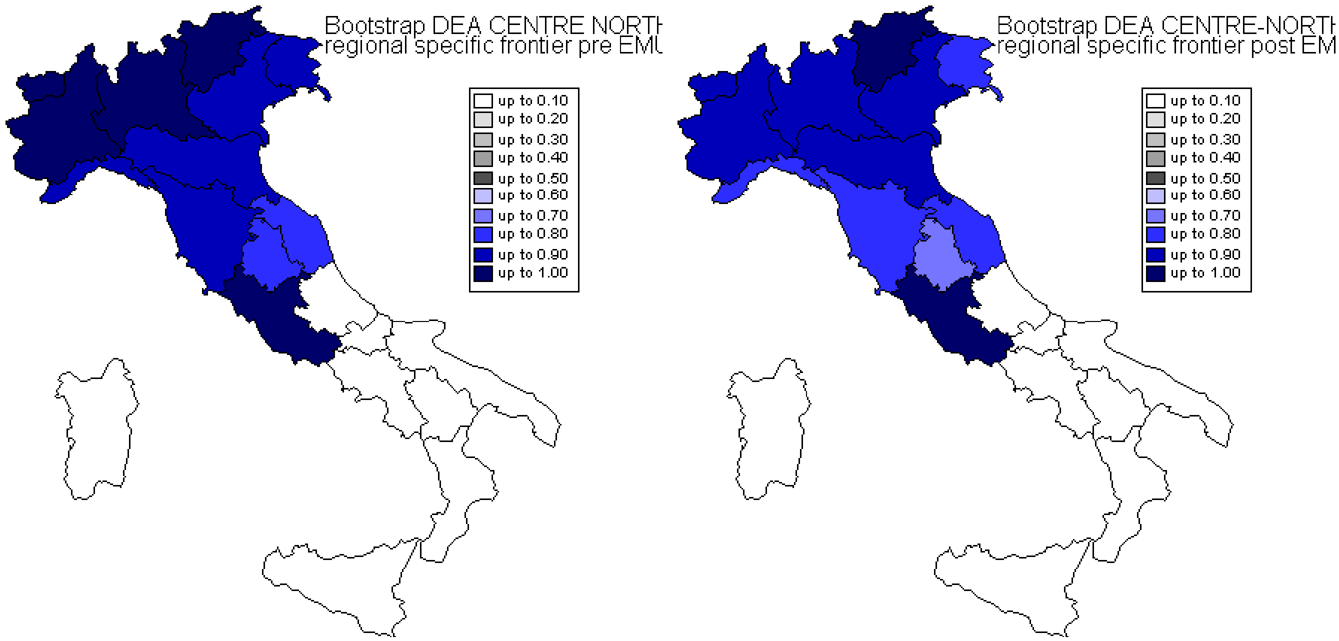

Figure 2: Bootstrap efficiency scores for the Centre-North Italian regions before and after EMU adoption.

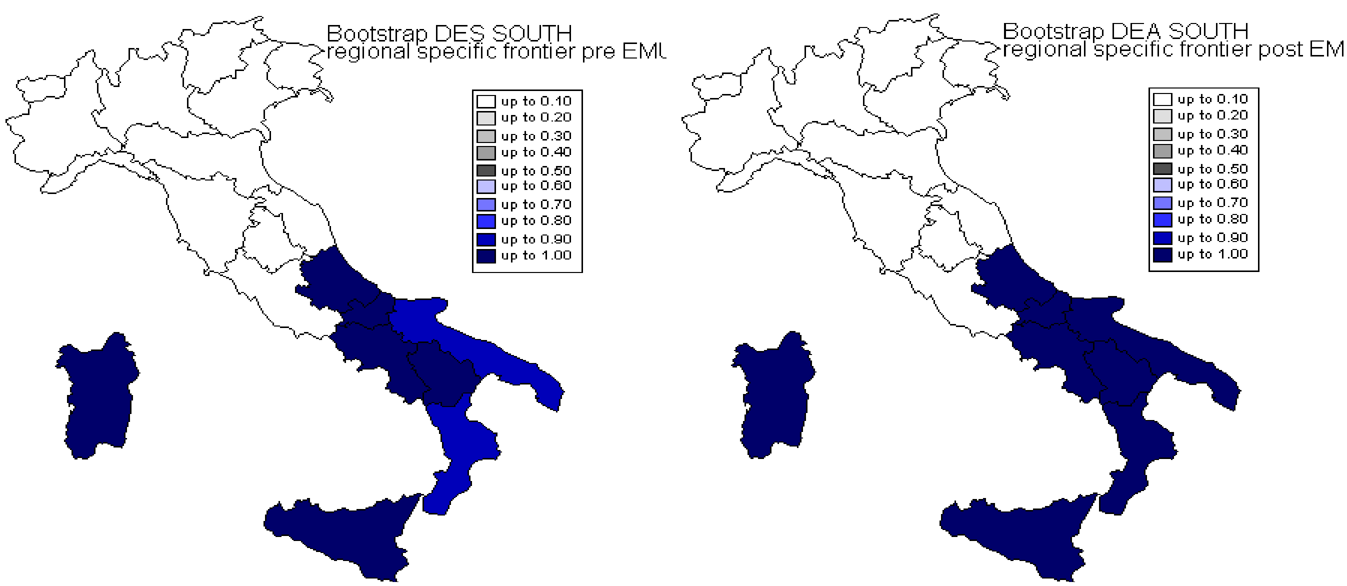

Figure 3: Bootstrap efficiency scores for the South Italian regions (NUTS 2) before and after EMU adoption.

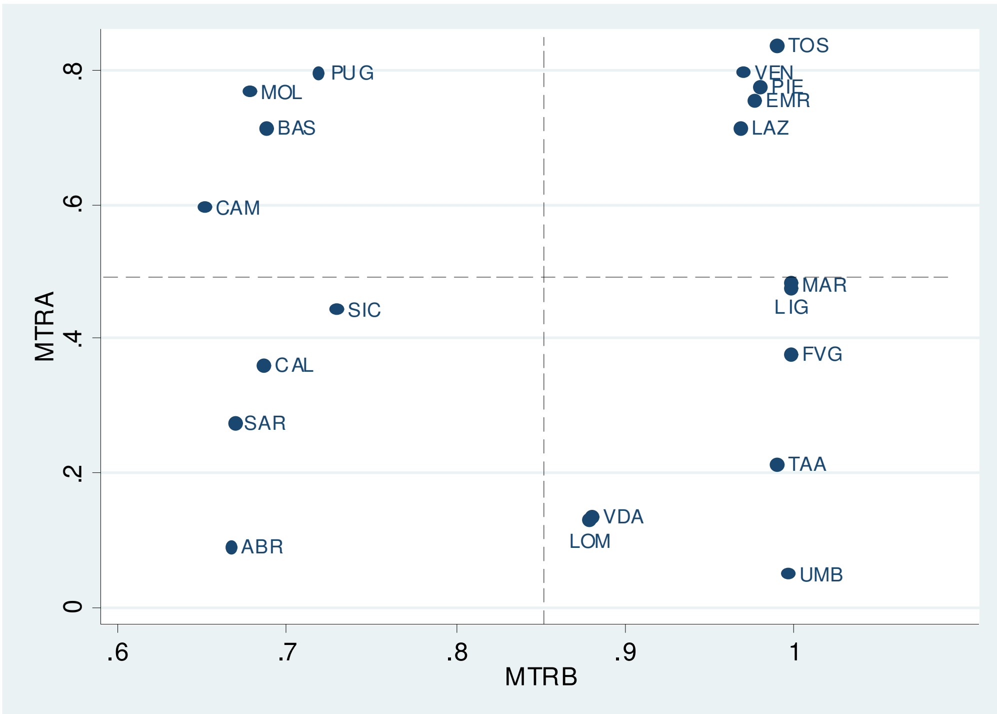

Figure 4: Metatechnology ratios of Italian regions before and after EMU adoption

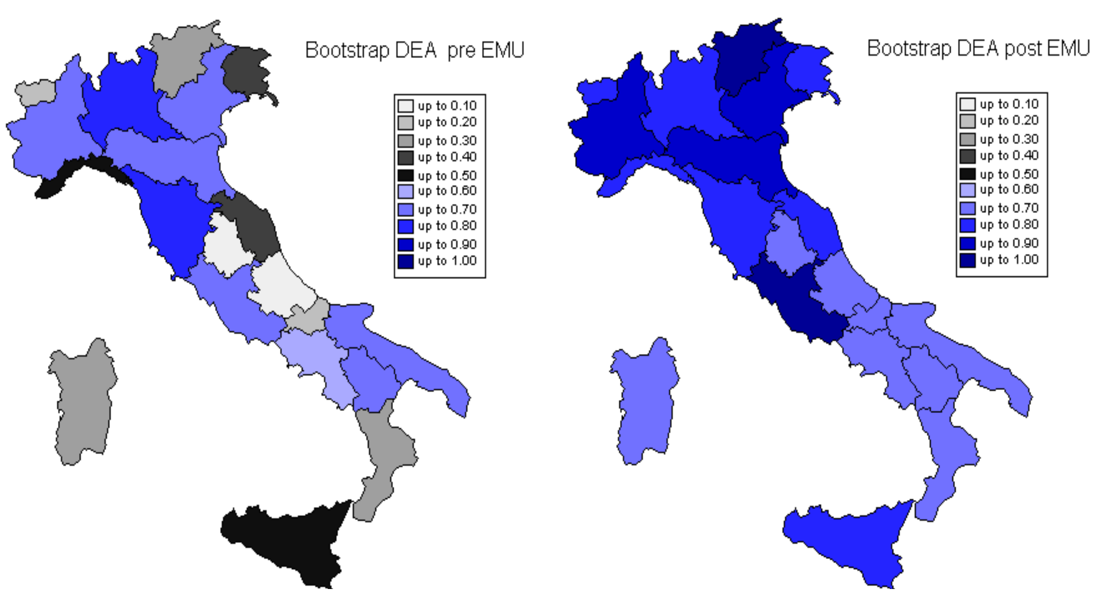

Figure 5: Bootstrap efficiency scores of all NUTS 2 Italian regions before and after EMU adoption.

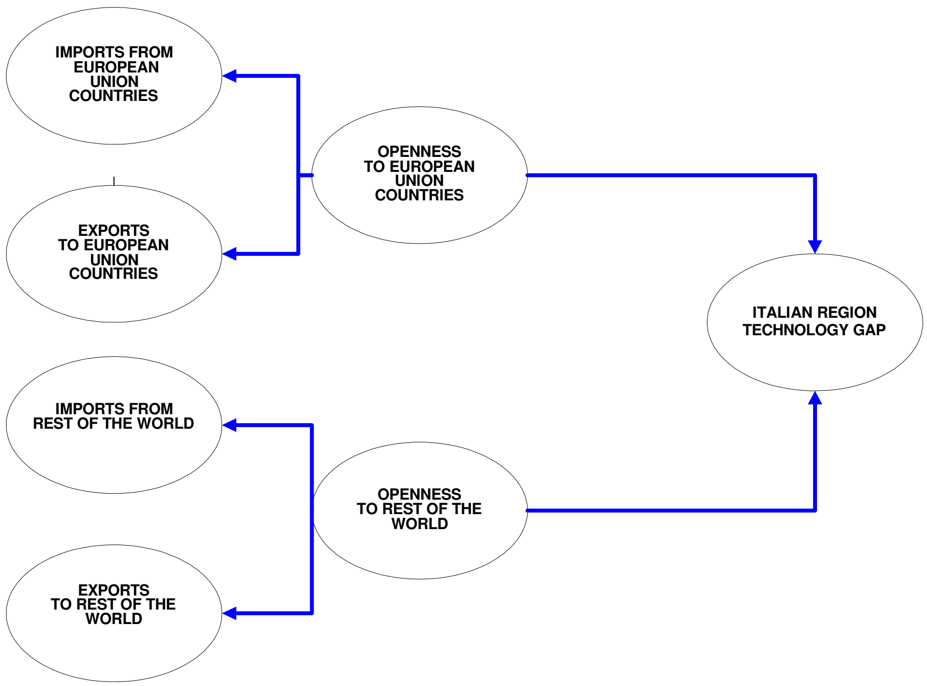

Figure 6: Structural model for TGs and its determinants.

8 APPENDIX II

Descriptive statistics of the used variables*

Output and Inputs Variables (Frontier Analysis)

Pre Adoption Period (1993-1999)			Post Adoption period (20		
Variable	Mean** (Std.Dev.)	Max (Min)	Variable	Mean (Std.Dev.)	M
Y*	48,357 (42,719)	225,436 (2,401)	Y*	63,661 (61,796)	30,61
L	1,049 (889)	3,911 (54)	L	1131 (974)	4351
K*	100,753 (71,731)	257,321 (10,909)	K	104,683(75321.46958)	277,4

Explanatory Variables (Regression Analysis)

Variable	Mean (Std.Dev.)	Max (Min)	Variable	Mean (Std.Dev.)	M
EXPUBL	9,290 (6543)	29,723 (638)	EXPUBL	14,582 (10,604)	47,85
TB25	24,939 (40502)	110,781 (-77,704)	TB25	69,435 (58,314)	774,6
TBW	9,045 (33102)	76,619 (-84,486)	TBW	28,576 (80,139)	1,010
RDEXP	142.30 (100.14)	434.7 (12.4)	RDEXP	233.71(134.02)	534.8

*Y, K, TB_{25} and TB_W are reported in Billions Euros

Table 1: Bootstrap DEA estimations for 1993-2011 period

	DEA	Bootstrap DEA	Bias	Sigma	LB	UB
			South Frontier			
ABR	0.958	0.945	0.013	0.000	0.920	0.967
BAS	0.948	0.926	0.022	0.000	0.899	0.947
CAL	0.918	0.904	0.014	0.000	0.880	0.921
CAM	1.000	0.959	0.041	0.001	0.916	0.958
MOL	1.000	0.960	0.040	0.001	0.916	0.967
PUG	0.961	0.936	0.025	0.000	0.903	0.927
SAR	0.931	0.917	0.014	0.000	0.893	0.954
SIC	1.000	0.959	0.041	0.001	0.918	0.942
Mean	0.964	0.938	0.026	0.000	0.906	0.948
Std.Dev	0.033	0.021	0.013	0.000	0.014	0.017
Min	0.918	0.904	0.013	0.000	0.880	0.921
Max	1.000	0.960	0.041	0.001	0.920	0.967
			North-Center Frontier			
FVG	0.802	0.768	0.034	0.000	0.736	0.799
FNG	0.802	0.768	0.034	0.000	0.736	0.799
LAZ	1.000	0.952	0.048	0.001	0.895	0.996
LIG	0.817	0.817	0.040	0.001	0.780	0.853
LOM	1.000	0.856	0.144	0.011	0.790	0.996
MAR	0.778	0.744	0.035	0.000	0.711	0.774
PIE	0.887	0.853	0.034	0.001	0.803	0.884
TAA	1.000	0.930	0.070	0.001	0.891	0.996
TOS	0.826	0.756	0.040	0.001	0.745	0.822
UMB	0.750	0.716	0.033	0.000	0.686	0.746
VDA	1.000	0.860	0.140	0.011	0.794	0.996
VEN	0.884	0.843	0.041	0.001	0.792	0.881
Mean	0.891	0.833	0.058	0.002	0.787	0.887
Std.Dev	0.092	0.071	0.041	0.004	0.063	0.092
Min	0.750	0.716	0.033	0.000	0.686	0.746
Max	1.000	0.952	0.144	0.011	0.895	0.996

Table 2: Bootstrap DEA estimations for both periods with respect to the region specific frontier

	Pre EMU adoption period						After EMU adoption period					
	DEA	Bootstrap DEA	Bias	Sigma	LB	UB	DEA	Bootstrap DEA	Bias	Sigma	LB	UB
South Frontier												
ABR	0.954	0.934	0.020	0.000	0.906	0.952	0.959	0.949	0.010	0.003	0.928	0.958
BAS	0.955	0.926	0.029	0.000	0.888	0.953	0.967	0.949	0.017	0.000	0.927	0.966
CAL	0.860	0.834	0.026	0.000	0.804	0.859	0.949	0.936	0.012	0.000	0.914	0.948
CAM	1.000	0.944	0.056	0.002	0.879	0.998	1.000	0.970	0.030	0.000	0.940	0.999
MOL	1.000	0.940	0.060	0.002	0.868	0.998	1.000	0.969	0.031	0.000	0.937	0.999
PUG	0.909	0.880	0.029	0.001	0.831	0.908	0.941	0.924	0.016	0.000	0.896	0.940
SAR	0.945	0.917	0.028	0.000	0.885	0.942	0.970	0.953	0.017	0.000	0.928	0.970
SIC	1.000	0.947	0.053	0.001	0.896	0.997	1.000	0.970	0.030	0.000	0.938	0.999
Mean	0.953	0.915	0.038	0.001	0.869	0.951	0.973	0.953	0.021	0.001	0.926	0.972
Std.Dev	0.050	0.039	0.016	0.001	0.035	0.049	0.024	0.017	0.008	0.001	0.015	0.024
Min	0.860	0.834	0.020	0.000	0.804	0.859	0.941	0.924	0.010	0.000	0.896	0.940
Max	1.000	0.947	0.060	0.002	0.906	0.998	1.000	0.970	0.031	0.003	0.940	0.999
North-Center Frontier												
EMR	0.971	0.895	0.076	0.000	0.856	0.919	0.905	0.863	0.042	0.001	0.806	0.901
FNG	0.907	0.888	0.019	0.000	0.862	0.904	0.759	0.720	0.039	0.001	0.684	0.755
LAZ	1.000	0.970	0.030	0.000	0.925	0.998	1.000	0.944	0.056	0.002	0.879	0.995
LIG	0.919	0.896	0.023	0.000	0.865	0.916	0.832	0.787	0.045	0.001	0.746	0.827
LOM	1.000	0.910	0.090	0.005	0.834	0.996	1.000	0.832	0.168	0.015	0.772	0.993
MAR	0.821	0.804	0.018	0.000	0.780	0.819	0.759	0.718	0.041	0.011	0.682	0.754
PIE	0.973	0.909	0.065	0.000	0.869	0.932	0.870	0.834	0.036	0.001	0.780	0.867
TAA	1.000	0.977	0.023	0.000	0.952	0.996	1.000	0.915	0.085	0.002	0.873	0.995
TOS	0.878	0.849	0.029	0.000	0.817	0.876	0.805	0.761	0.044	0.001	0.718	0.801
UMB	0.814	0.796	0.018	0.000	0.775	0.812	0.728	0.691	0.036	0.001	0.655	0.723
VDA	1.000	0.908	0.092	0.005	0.832	0.996	1.000	0.832	0.168	0.015	0.771	0.994
VEN	0.899	0.872	0.027	0.000	0.832	0.897	0.878	0.833	0.045	0.001	0.774	0.876
Mean	0.932	0.889	0.042	0.001	0.850	0.922	0.878	0.811	0.067	0.003	0.762	0.873
Std.Dev	0.069	0.055	0.029	0.002	0.052	0.066	0.104	0.078	0.049	0.005	0.070	0.103
Min	0.814	0.796	0.018	0.000	0.775	0.812	0.728	0.691	0.036	0.001	0.655	0.723
Max	1.000	0.977	0.092	0.005	0.952	0.998	1.000	0.944	0.168	0.015	0.879	0.995

Table 3: Bootstrap DEA estimations for 1993-2011 period

	DEA	Bootstrap DEA	TG	MTR
ABR	0.686	0.646	0.316	0.684
BAS	0.714	0.657	0.291	0.709
CAL	0.676	0.642	0.290	0.710
CAM	0.682	0.634	0.339	0.661
EMR	0.909	0.851	0.023	0.977
FNG	0.802	0.764	0.006	0.994
LAZ	1.000	0.922	0.031	0.969
LIG	0.857	0.812	0.006	0.994
LOM	1.000	0.742	0.132	0.868
MAR	0.778	0.740	0.005	0.995
MOL	0.768	0.656	0.316	0.684
PIE	0.887	0.836	0.020	0.980
PUG	0.702	0.669	0.285	0.715
SAR	0.690	0.651	0.290	0.710
SIC	0.761	0.719	0.250	0.750
TAA	1.000	0.920	0.010	0.990
TOS	0.826	0.775	0.013	0.987
UMB	0.750	0.711	0.008	0.992
VDA	1.000	0.746	0.133	0.867
VEN	0.884	0.818	0.030	0.970
Mean	0.819	0.746	0.140	0.860
Std.Dev	0.117	0.091	0.138	0.860
Min	0.676	0.634	0.005	0.661
Max	1.000	0.922	0.339	0.995

Table 4: Bootstrap DEA estimations, technology gaps and metatechnology ratios for both periods

	Pre EMU adoption period				Post EMU adoption period			
	DEA	Bootstrap DEA	TG	MTR	DEA	Bootstrap DEA	TG	MTR
ABR	0.100	0.085	0.910	0.090	0.672	0.632	0.333	0.667
BAS	0.896	0.662	0.285	0.715	0.707	0.653	0.312	0.688
CAL	0.350	0.301	0.639	0.361	0.679	0.643	0.313	0.687
CAM	0.862	0.563	0.404	0.596	0.678	0.633	0.348	0.652
EMR	0.969	0.676	0.245	0.755	0.905	0.843	0.023	0.977
FVG	0.400	0.336	0.622	0.378	0.759	0.718	0.002	0.998
LAZ	1.000	0.691	0.288	0.712	1.000	0.91	0.032	0.968
LIG	0.500	0.428	0.523	0.477	0.832	0.785	0.002	0.998
LOM	1.000	0.721	0.232	0.768	1.000	0.731	0.121	0.879
MAR	0.450	0.388	0.518	0.482	0.759	0.716	0.002	0.998
MOL	0.150	0.119	0.869	0.131	0.755	0.657	0.322	0.678
PIE	0.971	0.702	0.227	0.773	0.870	0.817	0.020	0.980
PUG	0.901	0.699	0.206	0.794	0.700	0.664	0.281	0.719
SAR	0.300	0.251	0.726	0.274	0.679	0.638	0.331	0.669
SIC	0.963	0.422	0.555	0.445	0.751	0.708	0.270	0.730
TAA	0.250	0.209	0.786	0.214	1.000	0.906	0.010	0.990
TOS	0.861	0.710	0.164	0.836	0.805	0.754	0.010	0.990
UMB	0.050	0.040	0.949	0.051	0.728	0.689	0.003	0.997
VDA	0.308	0.122	0.866	0.134	1.000	0.733	0.119	0.881
VEN	0.888	0.694	0.204	0.796	0.878	0.808	0.030	0.970
Mean	0.608	0.441	0.511	0.489	0.808	0.732	0.144	0.856
Std.Dev	0.349	0.246	0.272	0.272	0.120	0.088	0.147	0.147
Min	0.050	0.040	0.164	0.051	0.672	0.632	0.002	0.652
Max	1.000	0.721	0.949	0.836	1.000	0.913	0348	0.998

Table 5: Results of Friedman tests concerning the rank of TE, TG between the regions specific technologies and the metatechnology

Hypothesis Tested (H_0)	Criterion Value (p-value)	Decision with respect to H_0
TE rank for the North region is equal before and after EMU	19.692 (0.049)	Not accepted
TE rank for the South region is equal before and after EMU	13.01 (0.072)	Not accepted
MTE ranking didn't change before and after EMU	10.457 (0.275)	Not rejected
MTR ranking didn't change before and after EMU	20.171 (0.384)	Not rejected

Table 6: Results of Mann Whitney tests concerning on the differences of TE, TG between the regions specific technologies and the metatechnology

Hypothesis Tested (H_0)	Criterion Value (p-value)	Decision with respect to H_0
TE scores for the North region is equal before and after EMU	2.367 (0.017)	Not accepted
TE scores for the South region is equal before and after EMU	-2.521 (0.011)	Not accepted
MTE scores are equal before and after EMU	-3.92 (0.000)	Not accepted
MTR scores are equal before and after EMU	-3.621 (0.000)	Not accepted

Table 7: Determinants of Technology gaps for the two periods-Structural estimates

	Indicator	Weight	Loading	Communality (AVE)
	1993-2011 Period			
$OPEN_{25}$	Imports from EU	0.408	0.981	0.963
	Exports from EU	0.604	0.990	0.983
$OPEN_W$	Imports from rest of the world	0.437	0.942	0.927
	Exports from rest of the world	0.681	0.991	0.982
	Pre EMU adoption period			
$OPEN_{25}$	Imports from EU	0.59	0.987	0.974
	Exports from EU	0.504	0.981	0.972
$OPEN_W$	Imports from rest of the world	0.523	0.987	0.975
	Exports from rest of the world	0.491	0.986	0.972
	Post EMU adoption period			
$OPEN_{25}$	Imports from EU	0.889	0.884	0.713
	Exports from EU	0.537	0.563	0.714
$OPEN_W$	Imports from rest of the world	0.741	0.996	0.993
	Exports from rest of the world	0.469	0.974	0.949

Table 8: Determinants of Technology gaps for the three periods-Structural estimates

1993-2011 period		
Explanatory Variables	Variable	Coefficient (Asymptotic t-ratio)
	Constant	0.000 (7.68)*
Region Specific Characteristics	$OPEN_{25}$	-0.707 (5.93)*
	$OPEN_W$	-0.438 (4.67)*
R^2		0.973
GOF		0.908
Pre EMU adoption period		
	Constant	0.000 (6.74)*
Region Specific Characteristics	$OPEN_{25}$	-1.127 (5.32)*
	$OPEN_W$	-0.146 (6.94)*
R^2		0.969
GOF		0.917
Post EMU adoption period		
	Constant	0.000 (6.23)
Region Specific Characteristics	$OPEN_{25}$	-0.439 (-1.89)**
	$OPEN_W$	0.073 (0.030)
R^2		0.689
GOF		0.551

* One and **two asterisks denote statistical significance at 10% and 5% respectively.