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Regional efficiency and logistics development of the territory: an application to the Italian case

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Abstract

The efficiency and competitiveness of the territories with reference to logistics performance are factors of increasing importance for the economic recovery of the local production systems affected by the international crisis. These strategical elements can be analyzed by different econometric methods with parametric and non-parametric approaches. These studies fall in the mainstream economic analysis of regional frontiers to estimate the differentials of technical efficiency and economic efficiency between different territories where the technical efficiency reflects the capacity of obtaining an output to minimize the use of inputs and reduce waste of resources and economic efficiency is based on the ability to minimize the total cost of the input considering the market prices of production factors.
The article aims to highlight the links between freight traffic for the different modes of transport and spatial and environmental variables at territorial Italian NUT3 European level in order to measure the degree of regional logistics efficiency and subsequently to investigate about the main factors that determine the logistics efficiency. Through a two-stage model was first accomplished a regional analysis of stochastic frontier to determine the degree of technical efficiency in the generation and attraction of freight traffic and after the estimates produced as a result of the first stage have been tested through a Tobit regression consider others independent variables to investigate the environmental factors that can influence the regional logistics efficiency.
The empirical findings strongly confirm a positive role of some variables in improving logistics efficiency. The coefficients of these variables have an expected sign and also are statistically significant, with other regional characteristics being controlled for, when the logistics efficiency scores were regressed on it. In addition, the findings indicate that economies of agglomeration and of innovation, international openness degree and multimodal accessibility might add a strong positive function in the production of transport and logistics services.

Keywords: regional efficiency, sthocastic frontier, Tobit regression, logistics.

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1. Introduction

The evolution of the regional logistics systems requires the integration in localization strategies of firms at different spatial scales (local, regional, national, continental or worldwide scales). The downward trend in transport costs and improved efficiency in logistics have had an impact on the regional dynamics of industrial choices about localization of factories, depots, warehouses. The main network logistics problem has concerned, specially into the first phase of globalization process, the number and the dimensions of the logistics structures in relation to their localization to serve the markets.

Logistics is crucial in the location of production and the choice of distribution site especially among centralized models with few or no regional and peripheral facilities and decentralized models, in which levels of peripheral networks increase (warehouses, transit points, local shops) (McKinnon, 2009). Krugman, Fujita and Thisse have demonstrated the importance of logistics in a monopolistic competitive economic space were the optimal placements is strongly influenced by the relative costs of the specific regional market (Krugman, 1991, Fujita and Thisse, 2002).

The role of regional economies in national economies has changed significantly as a result of globalization. Until the recent past, regional economies tended to be highly specialized and integrated on a territorial scale in the production of goods and services based on local resources and expertise. The case of Italian mono-sectional clusters, called "distretti industriali", is well known as a model of regional development which has mainly affected the northern regions of the country. Some authors have defined this model as "Italianate industrial district" about the phenomena that in Italy in the 1970s there was a rediscovery of the Marshallian industrial district model, with the difference that participants were actively seeking socio-cultural cooperation through shared values that go beyond simple collaboration between the firms (Marchisio, 2006).

The decentralization and fragmentation of the production processes have made to become the choice about localization "spatial invariant" on the base of geographic positioning of the logistic activities where the summary of the costs associates to the movement of the goods in the space added to the costs associates to phases of handling and warehousing, can reaches equal result but with multiple combinations of localization in function of the production processes and the network configuration. In many industrial sectors the production unbundling is sometimes 'modularised', with parts coming together for assembly in a 'module' which is then shipped whole to the final assembly plant (Frigant, Lung 2002). Some authors make a first distinction between "snakes" and "spiders" production processes in which 'adjacency' is quite different. "Snakes" are production processes where a physical entity follows a linear process with value added at each stage. "Spiders"

are many limbed with parts from different sources coming together in one place for assembly. In practise the two are combined: spiders might be attached to any part of a snake, and multiple snakes might join into a spider. Interactions and collocation benefits may also extend beyond 'adjacent' stages in the value chain if, for example, there are synergies in design and product specifications. There are also the wider benefits of agglomeration, such as shared labor skills and knowledge spillovers (Baldwin, Venables, 2011).

This transformation of productive and market's order had origin initially by the great multinational enterprises but quickly it has been diffused also inside the Italian industrial system, included the small and medium enterprise and industrial districts that represent a large part of Italian economy. The localization of productive sites in function of the network model originates distribution models to serving various and larger regions. The enterprises organized at multinational level in order to reach spatial models to gain profits and the national vision loses importance. Models of international economics based to comparative advantages must be integrated with new tools of economic analyses that better represent the global market and the intra-manufacturers trades (Krugman, 1994).

Evidently, the principles of neoclassical economics, especially constant returns of scale and decreasing returns of capital, do not reflect the evolution of global markets. In more recent growth economics, these two factors have been removed and new production factors have been introduced, in particular human capital, technological and organizational efficiency. Thus up to 60% of per capita income differences can now be explained, whereas the traditional model only justified 25% (Seravalli, 2011).

Agglomeration processes of different production factors and products, and therefore externalities, increasing returns of scale and finally non-competitive markets, could thus take place. At the same time, solutions depended on the equilibrium of economic forces both in terms of concentration and in terms of dispersion. Increasing returns to scale tend to foster geographical concentration of production of each good. When transportation costs play a role, attractive locations for production are those which are close to markets and suppliers, other things being equal. Finally, concentration of production in some location tends to attract the mobile factors of production. Once a region has a high share of production, this pattern is likely to reinforce itself: a so-called second-nature advantage for the dominant region develops, that is, the region becomes attractive for firms because so many other firms already produce there (rather than because of superior resource endowment).

Freight transport and logistics activities in the new economy carries out a more complex and critical function because it is not limited to a simple transfer of things from a place to an other, from the producer to the consumer, but it is integrating part of the production process and its economic

organization. Moreover, the evolution of the modern economic systems has produced a new vision of the localization models through new network models where logistics integration and the strategic positioning contribute to generate added value (Chirstofer, 2005).
However, today among the most advanced countries, only few regions are unaffected by the change of international supply of goods and services. As a result of these changes, sub-national territorial entities have become more specialized, focusing on searching out external market opportunities, and being less integrated in local areas. Among the trends in the near future, the *European Logistics Association* (ELA) is paying special attention to the continuing process of globalization of European economies and its trade in goods, with particular regard to the increase in exports, as main growth factor for mature countries that will reap the benefits, and the increase in the regionalization of logistics to reduce costs and negative environmental effects (CO_2 *footprint*). Decentralized regional networks for logistics of ever more consolidated cargoes represent one of the strategic choices for recovery and for eluding the crisis in the European Union (ELA, AT Kearney, 2009). Faced with varying degrees of general efficiency of the territorial logistics system, different strategic solutions are made available which should be assessed with reference to each spatial feature and requirement of the economic activities.
The article is structured in the following way: the first is the introduction, the second section is dedicated to a brief excursus about the regional logistics efficiency and the research methods, the third one deals with the model of analysis of the regional logistics efficiency, the fourth section with data and variables, while the results are reported in the fifth section. Finally the concluding section contains some policy indications.

2. Regional logistics efficiency

Transport infrastructures affect accessibility, and hence the location of the production and distribution structures, specificity of products, areas in which companies work, phases and activities that characterize the production sectors, logistic networks, and proximity to markets. In addition to the profile of cost management by companies and their producers' surplus and profit, logistics involves questions of assessment of the effects on the transport system to be tackled by tools for economic analysis, specially with reference to the capacity of stay connected in a network.
In optimizing flows, the balance of supply and demand analysis is essential and should be continually sought for throughout all stages of the logistics, and should be such as to minimize the total cost. This cost being the summation of different costs of storage services and commercial exploitation of goods (stocks, warehouses, assembly, packaging, etc.) and costs of transport services

and handling terminals differs according to the adoption of different configurations of logistic network and different supply structures of consumer markets.

The innovations induced by the modern distribution systems, have evidenced as the transport infrastructure endowment has to necessarily be accompanied by adequate and efficient structures dedicated to logistics services, not only the traditionally ones such us warehousing and sorting, but more and more innovative and high tech services supporting the productions. For many Italian regions, from the point of view of the outsourcing of such functions, the situation still appears to be at a stage of substantial backwardness compared to the most modern strategic supply-chain. In many cases logistic structures are not organized according models of multi-services and multi-customers platforms that supporting the local productions and their fast and efficient outflow towards the national and international destinations. Generally they results fragmented in small units dispersed on the territory with remarkable limits to multimodal accessibility. The innovations induced by the modern distribution systems, have evidenced as the transport infrastructure endowment has to necessarily be accompanied by adequate and efficient structures dedicated to logistics services, not only the traditionally ones such us warehousing and sorting, but more and more innovative and high tech services supporting the productions.

Generally they results fragmented in small units dispersed on the territory with remarkable limits to multimodal accessibility. The starting point is that the quality of transport infrastructure in terms of capacity, connectivity, travel speeds etc. determines the quality of locations relative to other locations, i.e. the competitive advantage of locations which is usually measured as accessibility. Investment in transport infrastructure leads to changing location qualities and may induce changes in spatial development patterns (Espon, 2005).

The region's economic performance is strongly determined by the availability of immobile and polyvalent production factors. According to this approach deriving by a microeconomic view of the production function, a certain level of human and infrastructure capital can be considered a necessary precondition for a favourable regional development (Barro and Sala-i-Martin 1991).

Like the firm within the industrial organization, economic theory has tried to investigate and evaluate empirically the regional economies as entities using economic resources, applying the best technology and receiving some output through the production process. In keeping with this stylized vision of the region, it is consistent to expand and develop the assessment methods of industrial efficiency to regional efficiency (Puig-Junoy 2001).

The application of traditional production function methodology to spatial production units in order to find out the nature and strength of the explanatory variables, is not new, particularly when the independent variables used are labour and capital. But beyond the conventional wisdom in

production economics, territorial units unlike other manufacturing decision making units (DMU), represent a spatial production system that cannot be fully understood simply by the quantity of labour and capital alone. There is reasonable consensus among economists that the mobility of goods, services, and labour across regions depends largely on the quality and quantity of various integrated facilities available, and not directly and solely on the amount of investment or capital stock (Park, De, 2004).

There are two main concepts related to economic performance: productivity and efficiency. The concept of productivity is commonly defined as a ratio of the volume measure of output to the volume measure of input used, whereas efficiency is a relative concept, i.e. the performance of a unit of analysis (firm, transport terminal, etc.) is compared to a benchmark. Frontier represents the 'best possible practice' in the industry or sample studied. Once the frontier is estimated, efficiency then can be evaluated against the frontier. Efficiency comprises technical efficiency, scale efficiency and allocative efficiency. 'Technical efficiency' is defined as the relative production between the observed output and the best possible output. 'Scale efficiency' is defined as the relative scale between the observed firm size and the optimal firm size. 'Allocative efficiency' is a measure of the benefit or utility derived from a proposed or actual choice in the distribution or apportionment of resources (Wang, Cullinane and Song, 2005).

The formal definition of technical efficiency (TE) was given by Koopmans (1951), TE represents either the ability of a firm to minimise the inputs used in the production for a given output vector, or the ability of the firm to maximise the output from a given input vector. Therefore, there are two technical efficiency measures associated with the definition: an input-oriented measure and an output-oriented measure. The choice of measurement depends on the nature of the units. In the regional economic approach, a national or local government can influence the production level through development's policies and strategies, but the provision of transport infrastructures is difficult to change over a short-term period. This leads to the use of an output-oriented measure that features the maximum output able to be reached for a given input-mix.

This paper follows this line of thought and identifies the logistics efficiency of 103 Italian provinces of NUT3 level established by Eurostat in their use of infrastructures, physical and human private firm's capital. For this purpose, the so-called Stochastic Frontier Regional Analysis is applied (SFRA). This analysis should reveals a spatial pattern of regional efficiency but none information can be derived about the effect of others regional characteristic variables on the logistics regional efficiency. The regional characteristic variables are a kind of environmental factors which cannot be varied at the discretion of local government and the businesses but need to be taken into account in accomplishing relative efficiency evaluations. For this reason the analysis is carried out through a

two-stage approach. In a first stage, an SFRA is applied to identify the regions' logistics efficiency; the second stage seeks to decompose the efficiency by using a Tobit regression analysis.
In the first stage of the study the logistics economic performance is been considered like spatial technical efficiency that can be defined as the production of maximum output given the inputs and as at minimal use of inputs, given the output. Estimates of technical efficiency of Italian regional and sub-regional "territorial units" (Local Labour Systems - LLS) have been made by providing for Cobb-Douglas type functions of regional production, whose estimate of the efficiency parameters of the production factors is carried out by using econometric techniques of stochastic regional frontier to evaluate the impact of investments on public capital (infrastructures) and incentives for industrial firms (Bollino, Polinori, 2005; Bigerna, Polinori, 2008).

3. Two stages model of analysis of the regional logistics efficiency and its determinants

3.1 Stochastic frontier to measure the technical efficiency

Some quantitative approaches have been developed for the measurement of production efficiency. In terms of the frontier approach, however, two categories can be identified: parametric (deterministic and stochastic) and non-parametric approach. Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA) are the most commonly used methods. Both methods estimate the efficient frontier and calculate the technical efficiency relative. The DEA approach uses linear programming to construct a piece-wise frontier that envelops the observations of all unit and cannot use test hypothesis. An advantage of the DEA method is that multiple inputs and outputs can be considered simultaneously, and inputs and outputs can be quantified using different units of measurement. However, a strong point of SFA in comparison to DEA is that it takes into account measurement errors and other noise in the data. DEA does not identify the difference between technical inefficiency and random error. On the other hand SFA is a parametric approach and can only accommodate single output with multiple input and where the functional form of the production is assumed to be specified. SFA also allows other parameters of the production technology to be explored (Coelli et al., 2005). The advantages of this approach are that hypotheses can be tested with statistical rigour.
The stochastic frontier methodology involves two important choices: a) determination of the functional form; b) breakdown of the inefficiency error term. Although the determination of the exact form of the production function is possible for some situation, it is more difficult in many other situations. In these cases, it is necessary to use approximations to determine the production function such as the Cobb-Douglas or translog production function or a more general approach

based on Box-Cox transformation. Empirical observations may deviate from the border for the existence of measurement errors for all observed variables, These random effects are integrated through the stochastic frontier analysis by decomposing the error into two components (Aigner et al., 1977), an inefficiency component U_i and a random component V_i. The random component is assumed to follow a normal distribution, whereas the inefficiency component is assumed to follow a positively skewed distribution for a cost function and a negatively skewed distribution for a production function. The V_i are assumed to be distributed independently and identically, and U_i are assumed to be distributed independently of V_i. Therefore, the stochastic frontier analysis estimates a function that takes into account random error and a specific inefficiency component for each unit. The most common response model used is the multiplicative model:

$$Y_i = \exp(\beta_o) X_{i1}^{\beta_1} X_{i2}^{\beta_2} .....X_{ik}^{\beta_k} \exp(V_i) \qquad \text{i = 1,….,n} \quad \text{(n = number of unit)} \qquad (1)$$

where Y_i is the output, X_s are inputs, and V_i is iid $N\sim(0, \sigma^2{}_v)$, and captures uncontrollable factors in the process such as measurement error and other statistical noise.

This model is called the Cobb-Douglas production function but is often referred to as the constant elasticity model because of this important property of its exponent coefficients. This structural model can be linearized for OLS estimation purposes by taking the log of both sides.

Assuming Y_i >0 and X_{ik} >0 the model is:

$$\ln Y_i = \beta_o + \sum_{k=1}^{K} \beta_k \ln X_{ik} + V_i \qquad \text{i = 1,….,n} \qquad (2)$$

We could also use the Translog function introduced by Christensen, Jorgenson, and Lau (1971). Translog is a quadratic function with all arguments in logarithm. The first two groups of terms in Translog correspond to the Cobb-Douglas or log-linear specification; the second-order (the last group of) terms introduce non-linear relationships and cross-relationships among the variables into the model. This function allows for free elasticities of substitution and it can provide quadratic approximation to an unknown form of a twice continuously-differentiable function. Translog corresponds to a second order Taylor-series progression. But the results are not different to those one log linear Cobb-Douglas, so in this paper we will give the result of log linear Cobb-Douglas.

A generalized Box-Cox transformation function could be used which integrates a variety of functional forms and provides comparison by parametric tests. The generalized quadratic Box-Cox model, assuming input- biased technical change, can be written as:

$$\ln Y_i^{\lambda} = \beta_o + \sum_{k=1}^{K} \beta_k X_i^{\delta} + \sum_{j}^{K} \sum_{k=1}^{K} \beta_{jk} X_{ij}^{\delta} X_{ik}^{\delta} + V_i \qquad (3)$$

where the variables Y^{λ} and X^{δ} are the Box-Cox transformations of output and inputs, respectively, defined as: $Y^{\lambda} = \frac{Y-1}{\lambda}$ for $\lambda \neq 0$ and ln(*Y*) for $\lambda = 0$; $X^{\delta} = \frac{X-1}{\delta}$ for $\delta \neq 0$ and ln(*X*) for $\delta = 0$; where δ and λ are the transformation parameters to be estimated. Under appropriate parametric restrictions for the values of δ and λ, the generalized quadratic Box-Cox transformation yields the four locally flexible functional forms (i.e., Translog, generalized Leontief, normalized quadratic, squared-root quadratic). A production function is defined as the schedule of the maximum amount of output that can be produced from a specified set of inputs, given the existing technology. The problem is to determine empirically the maximum potential of a production unit. This means estimating the production possibilities frontier. The ratio of the observed to the maximum potential output obtainable from a particular set of inputs is the technical efficiency of a production unit. Note that the variables in the production function should be measured in physical units. In performance evaluation, monetary measures are often used in addition to, or instead of, physical measures.

Disregarding random error *V* we can focus on a best performance frontier function with errors representing only inefficiency effects. All the observed data points will deviate randomly and in the same direction from this function. We consider the double-log model deterministic statistical frontier (Parsons, 2004):

$$\ln(Y_i) = \beta_0 + \sum_{k=1}^{K} \beta_k \ln X_{ki} - U_i = \beta_0 + \sum_{k=1}^{K} \beta_k \ln X_{ki} + \ln TE_i \qquad \text{i = 1,…..,n} \qquad (4)$$

where Y_i is the output and $U_i \geq 0$ captures the effects of technical inefficiency. The technical efficiency, *TE* of the *ith* unit is determined by:

$$TE_i = \exp(-U_i) \qquad (5)$$

The technical efficiency of a unit lies between zero and one and will be inversely related to the inefficiency effect. Usually U_i is assumed to be distributed non-negative half normal or other distribution as exponential and U_i is iid $N^+(0, \sigma_U^2)$ but another single-tailed distribution could be assumed (Greene, 2003). Note that σ_U^2 is the variance of the normal distribution before truncation at zero to obtain the distribution of non-negative inefficiency effects, and is not the variance of *U*. The mean and variance for half normal *U*s are: $E(U) = \sigma_U \sqrt{\frac{2}{\pi}}$ and Var(*U*) = $\frac{\pi - 2}{\pi} \sigma_U^2$ respectively .

The deterministic frontier model could be estimated by maximum likelihood (Aigner, Chu, 1968), but the regularity conditions application of maximum likelihood needed to obtain asymptotic results are violated (Greene, 1980).

The main problem with deterministic frontier is that it does not allow for the usual random errors encountered in formulating a model. Deterministic approaches, furthermore, are extremely sensitive to outliers (Parsons, 2004). The problem with the classical regression model, on the other hand, is that it ignores truncated technical inefficiency errors. The solution is to consider a composed error model, independently proposed by Aigner, Lovell, and Schmidt (1977), the Stochastic Frontier Analysis (SFA):

$$\ln Y_i = \beta_o + \sum_{k=1}^{K} \beta_{ki} \ln X_{ik} + V_i - U_i \tag{6}$$

This model of a stochastic frontier has the following assumptions:

i) $V_i \approx iidN(0, \sigma_v^2)$;

ii) U_i is a non-negative variable accounting for inefficiency, iid, with $N(\mu_i, \sigma_u^2)$, truncated to zero to ensure non-negativeness;

iii) V_i and U_i are distributed independently of each other and of the regressor.

The technical efficiency is:

$$\ln TE_i = \ln Y_i - \ln Y_i^* = \ln(\frac{Y_i}{Y_i^*}) = -U_i$$

Technical efficiency measurement by frontier method is based on the assumption that a gap normally exists between an unit actual and potential levels of technical performance. Thus, the technical efficiency is measured as the ratio between actual output and the potential output. In stochastic frontier analysis, the assumption is that the production function of the fully efficient unit is known. Lovell (1993) has shown that econometric approaches like the stochastic frontier analysis can distinguish the effects of noise from the effects of inefficiency.

The error term is no symmetric but negatively skewed. Thus, while OLS does not generate the desired estimates of unity specific technical efficiency, it does provide a basis for a simple test of the presence of technical inefficiency in the data, which is indicated by negative skewness of OLS residuals.

Under these hypotheses it is taken into account that the residuals of the OLS have correct asymmetry and thus it is appropriate to use the maximum likelihood estimation (MLE) of the stochastic frontier. The first step in fact is to test the sign of the third moment (negative skewness) of the residual OLS associated with the sample (Waldman, 1982). If a normal plus half normal model is true the OLS residuals will be negatively skewed. Note that the skewness is an intrinsic characteristic in SFA where it is used as a measure of technical inefficiency.

Under the null hypothesis of zero skewness of the OLS, an appropriate test statistic is: $G_1 = \frac{\sqrt{n(n-1)}}{n-2} g_1$ where $g_1 = m_3/m_2^{3/2}$ and m_2 and m_3 are the second and third sample moments of OLS residuals respectively.

An appropriate test statistic is: $Z_{g1} = G_1/SES$ where $SES = \sqrt{\frac{6n(n-1)}{(n-2)(n+1)(n+3)}}$. Some authors suggest √(6/n) where *(SES)* is standard error of skewness. This statistic is asymptotically distributed as a standard normal random variable. The hypothesis test will be one sided, with the alternative hypothesis being negative skewness. Estimation of stochastic frontier is computationally facilitated by the use the re-parameterizations proposed by Battese and Corra (1977):

$$\sigma^2 = \sigma_V^2 + \sigma_U^2 \ and \ \gamma = \frac{\sigma_U^2}{\sigma_V^2 + \sigma_U^2} = \frac{\sigma_U^2}{\sigma^2} \qquad (7)$$

The parameter γ lies between 0 and 1. When γ goes to 0, the symmetric error component dominates the one-sided error component and the model is an OLS production function with no technical inefficiency. On the other hand, when γ goes to 1, one-sided error component dominates the symmetric error component and the model is the deterministic production function with no noise and the OLS estimates is less justified. However, γ is not equal to the ratio of the variance of technical inefficiency effects to the total residual variance. This latter measure of relative contribution $\gamma*$ is found by:

$$\gamma* \frac{(\frac{\pi-2}{\pi})\sigma_U^2}{(\frac{\pi-2}{\pi})\sigma_U^2 + \sigma_V^2} = \frac{\gamma}{\gamma + (1-\gamma)(\frac{\pi}{\pi-2})} \qquad (8)$$

The parameters of stochastic frontier function are estimated by the maximum likelihood method. Prediction of individual technical efficiencies involves the unobservable technical inefficiency effects *Ui*. The best predictor for *Ui* is the conditional expectation of *Ui*, given the value of $_i \ \varepsilon_i = V_i - U_i$. However, the expectation of the random variable is not equal to the function of the expectation of the random variable for a non-linear function. The best predictor of $\exp(-U_i)$ is found by:

$$E[Exp(-U_i!\varepsilon_i)] = \frac{1-\Phi(\sigma* + \gamma\varepsilon_i/\sigma*)}{1-\Phi(\gamma\varepsilon_i/\sigma*)} \exp\left(\gamma\varepsilon_i + \frac{1}{2}\sigma^{*2}\right) = \hat{TE}_i \qquad (9)$$

Where $\sigma^* = \sqrt{\gamma(1-\gamma)\sigma^2}$; $\varepsilon_i = \ln(Y_i) - X_i^{'}\beta$ and $\Phi(*)$ is the standard normal cumulative distribution (Battese, Coelli 1988). The unknown parameters are replaced by their ML estimates. One estimator of the sample mean of technical efficiency is the arithmetic average of these predictors for the

individual technical efficiencies. The construction of confidence intervals is given distributional assumptions about the random terms. TE_{i} is a monotonic transformation of U_{i}, therefore, the lower and upper bounds L_i and U_i of the $(1-\alpha)$ percent confidence interval for $u_i|w_i$ are translated directly into upper and lower bounds on $TE_i|\varepsilon_i = exp(-Ui)|\varepsilon_i$.

They are given by: $\mathrm{L_i} = \exp(-\mathrm{U_i} - \mathrm{z_L}\sigma^*)$ and $\mathrm{U_i} = \exp(-\mathrm{U_i} - \mathrm{z_U}\sigma^*)$ where the quantiles $\mathrm{z_L}$ and $\mathrm{z_U}$ are calculated as: $Pr(Z>z_L) = (\alpha/2)[1-\Phi(-U_i/\sigma^*)]$ and $Pr(Z>z_U) = (1-\alpha/2)[1-\Phi(-U_i/\sigma^*)]$.

Z follows a standard normal distribution, with Φ the standard normal cumulative density function (Horrace, Schmidt, 1996).

3.2 Explanations of efficiency differences: a two-stage model

The first stage involves the specification and estimation of the stochastic frontier production function and the estimation of technical inefficiency effects, assuming that these inefficiency effects are identically distributed. The second stage involves the specification of a regression model for predicted technical inefficiency effects. Since the dependent variable in any of its formulations is bounded by zero and one, i.e. is a model with censoring at both ends of the distribution, OLS is inappropriate and either the dependent variable must be transformed prior to estimation or a limited dependent variable estimation technique must be employed. The second way is to use a Tobit model which is suitable in those applications which dependent variable is continuous, but its range is constrained. The technical inefficiency effects U_i are frequently estimated in a first step and the determinants of inefficiency are obtained in a second-stage regression. However, this can induce both bias and inefficiency in the estimates. Therefore, inefficiency effects are simultaneously conditioned on several specific factors and estimated using the parameterisation with mean (Battese, Coelli, 1995):

$$\mu = \delta_o + \sum_{j=1}^{J} \delta_j Z_j \qquad (10)$$

where Z_j is a vector of observable explanatory variables; δ_o and δ_j are respectively a parameter and a vector of parameters to be estimated. Although the two step approach seems reasonable, assuming that any inefficiencies found can be explained by additional factors in a second stage contradicts the assumption of identically distributed inefficiency effects on the stochastic frontier in the first stage.

More specifically, the study transformed technical efficiency (TE) scores into technical inefficiency (TIE) score by using the follow formula:

$$TIE = \frac{1}{TE} - 1 \qquad (10)$$

and then applied the Tobit regression method to estimate the above equation. The technical inefficiency scores (*TIE*) take a value between 0 and infinity (Sung, 2004).

3.3 Hypothesis of interest

The main hypothesis of interest of SFA:

1) $H_0 : \beta_1 = ... = \beta_q = 0$ q< K

Additional null hypotheses of interest are:

2) The omission of U_i is equivalent to imposing the restriction specified in the null hypotheses i.e.

$H_0 : \gamma = \delta_0 = ... = \delta_J = 0$

This indicates that the inefficiency effects in the frontier model are not present (no efficiency).

The null hypothesis is $Ho\!: H_0 : \gamma = 0$ which specifies that technical inefficiency effects are not stochastic. We reject the null hypothesis of no technical inefficiency effects given the specifications of the stochastic frontier and inefficiency effect model.

If the parameter γ is zero (we accept null hypothesis) then the variance of the technical inefficiency effect is zero and so the model reduces to the traditional mean response function. Leaving a specification with parameters that can be consistently estimated using ordinary least squares.

Another question of particular interest is if the set of exogenous that affect technical efficiency (no inefficiency effect or no sub set partial inefficiency effect).

Thus a test of null hypothesis that $H_0 : \delta_1 = ... = \delta_J = 0$ is conducted.

Null hypotheses of interest are tested using the generalized likelihood ratio. The generalized likelihood-ratio statistic λ given by:

$$\lambda_W = -2\ln[L(H_o)/L(H_1)] = -2[\ln(H_o) - \ln(H_1)] \qquad (11)$$

where $L(H_0)$ and $L(H_1)$ are the values of the likelihood function under specifications of the null and alternative hypotheses, H_o and H_1 respectively. In most cases, if the hypothesis is true, then λ has an approximately chi-square distribution. Special care, however, must be taken with any likelihood test involving a null hypothesis that includes γ = 0. When all unit are technically efficient, the true parameter vector is on the boundary of the parameter space. Consequently, the asymptotic distribution involves a mixture of chi-square distributions instead of a chi-square distribution (Coelli 1995;). Critical values of this mixed chi-square distribution are given in Kodde and Palm 1986.

4. Data and variables

The empirical analyses were carried out with cross-sectional data from Italian official source. In particular: the Italian Institute of Statics (Istat), the Tagliacarne Istitute, Infocamere, Italian Ministry of Economic Development, Italian Ministry of Territorial Cohesion. The study focuses on the intermediate level of local governments to obtain more degrees of freedom. In particular, it uses data on 103 provinces (NUT3 of the EU). The time span encompassed by the study is 2006, 2007 2008, 2009 and 2010 depending on the variables.

The analysis of technical efficiency is based on a total of four variables, but the output dependent variable, 'total freight traffic', is expression of other four variables relative each to a mode of transport (road, rail, sea and air) and also the independent variables 'infrastructural endowment' is composed by other four variables relative each to a mode of transport (road, rail, sea and air).

Together with the input and output variables for the SFRA, in order to investigate the possible factors influencing the efficiency estimates produced as outputs from the SFRA additional data are collected to facilitate the supplementary Tobit regression analysis. These data relate to specific territorial characteristics are collected for each Italian province. The Tobit regression analysis which is performed within this work on the outputs from the SFRA explicitly addresses the specific influence of others local factors which go beyond the allocation of production factors like capital and labor on regional efficiency estimates. Table 1 provides the definition of all the variables the present study uses.

Table 1 – Definition of Input, Output and Environmental variables

Type of variable	Definition	Source	Year	Unit
Output SFRA	Road freight traffic	ISTAT	2010	Tons
Output SFRA	Rail freight traffic	ISTAT	2010	Tons
Output SFRA	Air freight traffic	Assaeroporti	2010	Tons
Output SFRA	Port's freight traffic	Assoporti	2010	Tons (with the exclusion of the liquid bulk)
Input SFRA	Roads endowment index	Tagliacarne/Unioncamere	2010	Index Italy=100
Input SFRA	Rails endowment index	Tagliacarne/Unioncamere	2010	Index Italy=100
Input SFRA	Airports endowment index	Tagliacarne/Unioncamere	2010	Index Italy=100
Input SFRA	Ports endowment index	Tagliacarne/Unioncamere	2010	Index Italy=100
Input SFRA	Net fixed assets of transport and logistics firm sector	ISTAT/Mediobanca	2006-2010 average	Euro
Input SFRA	Transport and logistics employees	ISTAT	2010	Nr. (two digits ATECO 2007 codes: 49, 50, 51, 52, 53)
Environmental	Accessibility by road index	ESPON	2006	Travel time road accessibility NUT3 UE level (UE27=100)
Environmental	Accessibility by rail index	ESPON	2006	Travel time rail accessibility NUT3 UE level (UE27=100)
Environmental	Accessibility by air index	ESPON	2006	Travel time road accessibility NUT3 UE level (UE27=100)
Environmental	Multimodal accessibility	ESPON	2006	Travel time multimodal accessibility NUT3 UE level (UE27=100)
Environmental	Export index	Unioncamere	2010	Export/Total Value Added (%)
Environmental	Transport and warehouse sector's firms	ISTAT	2010	Nr. (two digits ATECO 2007 codes: 49, 50, 51, 52, 53)
Environmental	Patents intensity	ISTAT	2009	Nr. of patents registered to the EPO for millions of inhabitants
Environmental	Industrial value added sector	ISTAT	2008	Euro
Environmental	Commerce, transport and communication value added	ISTAT	2008	Euro

5. Main results

5.1 Measurement of regional efficiency

The study estimates two main models about the regional efficiency, for the first model is been consider as composite output variables the multimodal traffic originated and delivered in each Italian province and as composite input variable the total infrastructural endowment in addition to firm's capital and employees, while for the second model is been consider only the road traffic

considering that in Italy it is the dominant mode of freight traffic and as composite input variable the total infrastructural endowment in addition to firm’s capital and employees.

Before using the procedure of maximum likelihood the skewness of the residual OLS was verified, being equal to -0.5556 in the model 1 and -0.4780 in the model 2.Using the test $Z_{g1} = G_1/SES$ we reject the null hypothesis of zero skewness. The negative sign implies that the residuals of the sample have the correct characteristic for the implementation of the procedure of maximum likelihood. Table 2 presents the findings of the estimation of the maximum likelihood Exponential distribution for the inefficiency term witch is resulting more significative between half-normal, truncated normal an exponential tested models. We started with the model including all variables and interactions. The choice of the functional form has been carried out using the generalized quadratic Box-Cox, the criterion *BIC* and *AIC* and hypothesis of interest for the choice of the parsimonious model. The same strategy has been used for Tobit model. For reasons of space were not included in the text , but we will consider the final model.

The choice of the functional form has been carried out using the generalized quadratic Box-Cox, the hypothesis of interest and the criterion *BIC* and *AIC* for the choice of the parsimonious model and the interpretation of the parameters. The same strategy has been used for Tobit model. For reasons of space were not included in the text but we will consider the final model.

Table 2 - MLE Exponential Estimations of the Production Function – Models 1 and 2

Model 1 - Dependent Variable: *lnY*$_i$ (natural logarithm of the multimodal traffic)	Value	SD	Z	Pr > | z |
Constant	8.1811	0.4115	19.88	0.000
ln Infrastrucutral endowment	0.0862	0.0414	2.08	0.037
ln Net fixed firm's capital	0.2750	0.1502	1.83	0.067
ln Employees transport and logistics	0.7053	0.1363	5.17	0.000
Observations	103			
σ^2	0.1624***	0.034		
$\lambda = \sigma_u / \sigma_v$	1.8215***	0.084		
$\gamma = \sigma_u^2 / \sigma^2$ *with* $\sigma^2 = \sigma_u^2 + \sigma_v^2$	0.7684			
Log likelihood	-41.226585			
Model 2 - Dependent Variable: *lnY*$_i$ (natural logarithm of the road traffic)	Value	SD	Z	Pr > | z |
Constant	8.8134	0.3997	22.05	0.000
ln Infrastrucutral endowment	-0.0802	0.0403	-1.99	0.047
ln Net fixed firm's capital	0.3678	0.1355	2.71	0.007
ln Employees transport and logistics	0.6453	0.1197	5.39	0.000
Observations	103			
σ^2	0.1858***	0.0422		
$\lambda = \sigma_u / \sigma_v$	2.4311***	0.0886		
$\gamma = \sigma_u^2 / \sigma^2$ *with* $\sigma^2 = \sigma_u^2 + \sigma_v^2$	0.8552			
Log likelihood	-43.204024			

*** significance level at 1%; ** significance level at 5%; * significance level at 10%.

Table 2 summarizes the estimation results obtained for the stochastic frontier. The ratio of the variability for u_i and v_i can be used to measure a relative inefficiency. The values of λ and γ reveal for the two models that inefficiency plays an important role in the composite error term and postulate the choice of the stochastic frontier approach in the present study. The two models proves to be significant at the l% level. The coefficients of the variables are positives except in the case of the infrastructural endowment in the model 2. This is predictable because the variable consider all the modal infrastructure of the territory while the freight traffic considered is only the road mode. The value of λ is significant and therefore the adaptation with the distribution adopted (exponential) is satisfactory and the inefficiency is the main source of deviation from the output expected. Moreover, the value of the relationship of the variances γ of the component u_i and of the component $u_i + v_i$ is equal to 76.84% for the model 1 and 85.52% for the model 2 and indicates that the variation of the output among the territorial units is due to the difference in technical efficiency in both models. The null hypothesis $H_0 : \sigma_u^2 = 0$ is rejected for both models. The significance of SFRA models has emerged and the significant variables identified may be considered as a valid proxy for "regional system" production factors with reference to the capacity of movement of goods

traffic. Tabels 3 and 4 shows the technical efficiency scores for each Italian province calculated by applying the SFRA two models considering different output oriented data analysis.

Table 3 – Technical efficiency Scores by Italian Provinces – Models 1

Province	TE	Province	TE	Provincia	TE
AG	0.4797	GE	0.6244	PZ	0.7716
AL	0.6451	GO	0.8749	RA	0.9129
AN	0.6518	GR	0.8402	RC	0.9128
AO	0.6001	IM	0.6115	RE	0.8838
AP	0.7616	IS	0.8431	RG	0.4685
AQ	0.8106	KR	0.8022	RI	0.4847
AR	0.8657	LC	0.8200	RM	0.3380
AT	0.8154	LE	0.6689	RN	0.8927
AV	0.3252	LI	0.8978	RO	0.9189
BA	0.6553	LO	0.6685	SA	0.5203
BG	0.6631	LT	0.4413	SI	0.8890
BI	0.7378	LU	0.8512	SO	0.8491
BL	0.8792	MC	0.8022	SP	0.8523
BN	0.3504	ME	0.5338	SR	0.3736
BO	0.8532	MI	0.7943	SS	0.7977
BR	0.8667	MN	0.7640	SV	0.6234
BS	0.8450	MO	0.8859	TA	0.9386
BZ	0.9370	MS	0.8839	TE	0.8759
CA	0.7591	MT	0.7244	TN	0.9260
CB	0.8849	NA	0.4073	TO	0.8425
CE	0.3139	NO	0.7085	TP	0.4097
CH	0.7180	NU	0.7548	TR	0.8319
CL	0.4987	OR	0.6702	TS	0.8447
CN	0.8528	PA	0.3871	TV	0.8875
CO	0.7991	PC	0.8531	UD	0.8487
CR	0.8270	PD	0.8661	VA	0.4719
CS	0.8012	PE	0.8343	VB	0.7960
CT	0.4842	PG	0.9083	VC	0.7689
CZ	0.6514	PI	0.7852	VE	0.8264
EN	0.5256	PN	0.9177	VI	0.9067
FC	0.9245	PO	0.8519	VR	0.8025
FE	0.9263	PR	0.7746	VT	0.3981
FG	0.7137	PT	0.8741	VV	0.7967
FI	0.7369	PU	0.8701		
FR	0.3590	PV	0.8310		

Table 4 – Technical efficiency Scores by Italian Provinces – Models 2

Province	TE	Province	TE	Province	TE
AG	0.4480	GE	0.4547	PZ	0.7021
AL	0.6810	GO	0.8843	RA	0.9174
AN	0.6274	GR	0.8724	RC	0.6278
AO	0.5591	IM	0.5842	RE	0.8894
AP	0.7390	IS	0.8488	RG	0.3960
AQ	0.8369	KR	0.8186	RI	0.4727
AR	0.8819	LC	0.7729	RM	0.3462
AT	0.8190	LE	0.6025	RN	0.9321
AV	0.3090	LI	0.7968	RO	0.9233
BA	0.5989	LO	0.6782	SA	0.3924
BG	0.8369	LT	0.4052	SI	0.8853
BI	0.8819	LU	0.8701	SO	0.8048
BL	0.8190	MC	0.7290	SP	0.4666
BN	0.3090	ME	0.3399	SR	0.3490
BO	0.5989	MI	0.7755	SS	0.6093
BR	0.7129	MN	0.7094	SV	0.4699
BS	0.8240	MO	0.8875	TA	0.6018
BZ	0.9435	MS	0.8888	TE	0.8955
CA	0.5354	MT	0.6837	TN	0.9280
CB	0.8956	NA	0.3285	TO	0.8111
CE	0.3159	NO	0.7375	TP	0.4530
CH	0.7893	NU	0.6914	TR	0.8776
CL	0.4678	OR	0.6385	TS	0.8777
CN	0.8311	PA	0.2807	TV	0.8974
CO	0.7364	PC	0.8820	UD	0.8326
CR	0.8058	PD	0.8806	VA	0.6185
CS	0.8472	PE	0.8857	VB	0.7795
CT	0.3897	PG	0.9188	VC	0.8020
CZ	0.6904	PI	0.8342	VE	0.8771
EN	0.4768	PN	0.8974	VI	0.9107
FC	0.9410	PO	0.7852	VR	0.8269
FE	0.9354	PR	0.8144	VT	0.4044
FG	0.7190	PT	0.8831	VV	0.8556
FI	0.7720	PU	0.8709		
FR	0.3532	PV	0.8219		

5.2 Tobit models estimation

Tables 5 provide Tobit regression results for regional technical logistics efficiency estimated into two regression models. The difference between the two models is the use of technical inefficiency scores as a dependent variable, respectively, estimated with reference of the multimodal freights

traffic for the model 1 and road freight traffic in the model 2. As explained before, the independent variables are a kind of environmental variables which can explain some important relation with the regional logistics efficiency.

In table 3 most coefficients are consistent with *a priori* expectations. For example, the presence of transport and warehouse's sector firms, the exportation propensity, the innovation propensity (nr. of patents) and the multimodal accessibility tends to be positively and significantly linked and correlated with the multimodal logistics technical efficient score of the model 1. In the model 2, the variables exportation propensity, innovation propensity (nr. of patents), the multimodal accessibility and the road accessibility tends to be positively and significantly linked and correlated with the road logistics technical efficient score.

Table 5 – Tobit regional efficiency regression – Models 1 and 2

Model 1 - Dependent Variable: TIE_i (multimodal freight traffic)	Value	SD	t	Pr > | t |
Constant	-10.3876	4.4561	-2.33	0.022
ln Transport and warehouse firms	-0.3661	0.1893	-1.93	0.056
ln Export propensity	-0.0764	0.0364	-2.09	0.039
ln Rail accessibility	0.6611	0.3793	1.74	0.085
ln Road accessibility	-0.5946	0.4186	-1.42	0.159
ln Air accessibility	3.8923	1.1470	3.39	0.001
ln Multimodal accessibility	-4.3301	1.2389	-3.5	0.001
ln Patents (EPO)	-0.1186	0.0477	-2.48	0.015
ln Industrial value added	0.0321	0.1365	0.24	0.814
ln Commerce, transport and communication value added	0.4988	0.2164	2.3	0.023
Observations	103			
σ	0.3995	0.0278		
LR $\chi^2(9)$	48.71			
Prob > χ^2	0.000			
Pseudo R^2	0.3204			
Log likelihood	-41.2265			
Observations summary: *0 left-censored observations Y<=0* *103 uncensored observations* *0 left-censored observations*				
Model 2 - Dependent Variable: TIE_i (road freight traffic)	Value	SD	t	Pr > | t |
Constant	-10.3879	4.9925	-2.08	0.040
ln Transport and warehouse firms	-0.3111	0.2121	-1.47	0.146
ln Export propensity	-0.0963	0.0408	-2.36	0.021
ln Rail accessibility	0.7338	0.4250	1.73	0.088
ln Road accessibility	-0.7724	0.4690	-1.65	0.103
ln Air accessibility	3.3801	1.2851	2.63	0.010
ln Multimodal accessibility	-3.7034	1.3881	-2.67	0.009
ln Patents (EPO)	-0.1660	0.0535	-3.1	0.003
ln Industrial value added	-0.0628	0.1529	-0.41	0.682
ln Commerce, transport and communication value added	0.5895	0.2424	2.43	0.017
Observations	103			
σ	0.4476	0.03118		
LR $\chi^2(9)$	60.92			
Prob > χ^2	0.000			
Pseudo R^2	0.3247			
Log likelihood	-63.3655			
Observations summary: *0 left-censored observations Y<=0* *103 uncensored observations* *0 left-censored observations*				

For both models the likelihood ratios of 48.71 and 60.92 with the associated *p*-value ugual to 0.000 suggest that, at the 1% level of significance, some statistically significant relationship exists between the set of input variables and the regional logistics efficiency estimates considered like

dependent variable. In table 5, the coefficients that have a negative sign and are mostly statistically significant and have the right interpretation, in fact, it must be emphasized that the dependent variable is not technical efficiency score but technical inefficiency score (TIE_i).

The direction of the relationship between the hypothesized causal factors (the independent variables) and the transformed efficiency values (the dependent variable) is in line with what might be expected. Because of the transformation made, based on equation (3), a full efficiency estimate of 1.00 becomes 0.00, and measures less than unity take positive values up to infinity. Therefore, the higher the value of the transformed variable, the greater is the level of inefficiency (Demirel, Cullinane, Heralmbides, 2012).

The empirical results of the model 1 confirm the importance of the chosen variables to analyzes external causes of logistics efficiency of the territorial unit investigated. In particular, the number of firms included in the transport and warehouse statistical sector is found to be statistically significant at the 5% significance level. This provides support for the hypothesis that an agglomeration economic effects exist relate to the greater logistics efficiency. Considering the road freight traffic in the model 2 this effect seems to diminish its significance. The exportation propensity, is similarly found to be statistically significant at the 5% level in the both models, therefore this variables con be consider an strong determinant of regional logistics determinants and this is true in relation of the international openness degree of the territorial unit. The empirical findings strongly confirm a positive role of travel time multimodal accessibility at the NUT3 UE level estimate in the Espon study (Espon, 2009) in improving logistics efficiency as was to be expected. The coefficients of this variable have a expected sign and also are statistically significant in both models at the 1% significance level. In addition, the findings indicate that economies of innovation may represent a factor of incentive to the logistics efficiency in fact the most innovative companies typically have more international relationships and make better use of the logistic functions. The number of patents registered to the European Patent Office (EPO) is found to be statistically significant at the 1% significant level in the both models. Others regional characteristic control variables are find statistically significant but with a positive signs like rail accessibility, air accessibility and the value added of the economic sector commerce, transport and communication in the two models. Road accessibility is slightly significant particularly in the model 2, while the only variable that is statistically insignificant in both models is the industrial economic sector vale added.

6. Conclusion

This study attempts to evaluate the logistics performance of Italian NUT3 of the European territorial classification, called Provinces, by measuring their technical efficiency and, more importantly, to

examine the effects of some variables used like proxies of local characteristic on the logistics performance. The study is different from existing studies in that it uses a two stages model to investigates into the effects of regional logistics efficiency. The empirical analyses were carried out with cross-sectional data on 103 Italian provinces over the period 2006-2010. In particular, Stochastic Frontier Analysis techniques were applied to calculate technical efficiency scores and Tobit regression to investigate the possible causes of it for each local context. A limit of the analysis of technical efficiency with stochastic frontiers is in fact that they do not identify the root causes of the (in) efficiency, therefore, the objective of this study is precisely to determine and measure the degree of potential influence of some "environmental" variables on the regional level of logistics efficiency with respect to the generation/attraction of multimodal freight traffic. Through the application of Tobit regression analysis, the economies of agglomeration and of innovation, the international openness degree and the multimodal accessibility of the Italian provinces has been found to be statistically significant in explaining regional logistics efficiency estimates.

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