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Abstract

The level of interest in smart cities is growing, and the recent literature on this topic (Holland, 2008; Caragliu et al., 2009, Nijkamp et al., 2011 and Lombardi et al., 2012) identifies a number of factors that characterise a city as smart, such as economic development, environment, human capital, culture and leisure, and e-governance. Thus, the smartness concept is strictly linked to urban efficiency in a multifaceted way. A seminal research for European policy conducted by Giffinger et al. (2007) defines a smart city on the basis of several intangible indicators, such as a smart economy, smart mobility, smart environment, smart people, smart living, and smart governance. These authors' methodology results in a ranking of 70 European cities in terms of their smartness. Our aim is to verify the robustness of these smartness indicators in explaining the efficiency of the same sample of European cities. Using the concept of output maximising, we built a stochastic frontier function in terms of urban productivity and/or urban efficiency by assessing the economic distance that separates cities from being smart. Moreover, this approach, which distinguishes between inputs and efficiency, allows us to incorporate the smartness indicators into the systematic component within the error term. As a result, our conclusions identify a different ranking of European cities with respect to Giffinger et al. (2007)'s analysis, thereby highlighting the need for a better and more robust definition of these indicators.

Keywords: smart cities, stochastic frontier, technical inefficiency

JEL classification: D63, Q01, R11

1. Introduction

With half of the world's current population living in cities, the urbanisation process is still present in all countries. At the beginning of the 20th century, cities with 8 or 10 million inhabitants were unimaginable, as well as unmanageable. Sociologists and urban planners believed that the growth of cities should be limited and alternative solutions should be offered. These hypotheses, however, have been overridden by reality as city populations continue to increase. More recently, some scholars, such as Sassen (2004), emphasise the phenomena of the irreversibility of a city's growth and of the centrality of cities being the engine of development. Nonetheless, there are certain negative aspects regarding cities. First, they consume approximately 80% of the energy produced in a country. Second, they represent the place where the majority of communication occurs. Third, they are the primary source of pollution. For all of these reasons, making cities more livable and more efficient is rapidly becoming the most important, and no-longer postponable, objective of policy makers.

Several actions can be pursued to reach this target. The majority of these measures are related to specific physical, logistical, cultural and economic conditions of each city, even though, in general, the actions should be radical and "heavy", implying significant financial resources and time. In recent years, the concept of a "smart city", which implies lighter and less expensive approaches, has been developed.

The smart city's concept was introduced among the European Union's keywords in 2009 as part of the SET (Strategic Energy Technology) Plan. The SET indicates that a smart city is a city, or a large conglomerate, that aims to improve energy efficiency by undertaking as a target the double level, i.e., 20/20/20, as determined by the EU. However, the notion of a smart city and its subsequent definition were developed before the SET Plan. The idea of smart city is linked to the concept of innovation as the engine for development and to the concept of economic, social and environmental sustainability as targets for which to aim. These targets are strongly linked to the level of human capital and education – or, in the jargon of Florida (2002), to the creative class – in the urban context. Berry and Glaeser (2005, 2006) show, for example, that innovation is driven by industries and products that require an increasingly more skilled labour force.

Starting from this framework the aim of our paper is to verify the robustness of the Giffinger et al. (2007) smartness indicators in explaining the efficiency of the same sample of European cities. Using data of the Urban Audit Eurostat dataset, we have applied the stochastic frontier approach to estimate the production function of a selected European city bundle. On the basis of this approach, we have separated production inputs such as physical and human capital from efficiency/inefficiency factors influenced by the Giffinger et al. (2007)' smartness indicators. Moreover, we have disentangled distances from the efficient frontier by dividing the error component into two aspects: the systematic and the noise components. Finally, we have ranked the European cities on the basis of the estimated technical inefficiency.

The increasing importance of the quality of life within a city is mainly related to the economic development of an area. Our results tend to confirm this linkage. For this reason, only an efficient city has the requisites to be a focal point for a skilled labour force, businesses, students, tourists, etc. Our empirical estimation finds that northern Europe (German and UK cities) has the most efficient or smart cities.

The paper is organised as follows. The second section provides the background literature on smart cities. In the third section, we describe the methodology used, and in the fourth section, we illustrate our specification of the stochastic frontier approach. The fifth section reports data analysis and empirical results. Finally, we present our paper's conclusions in section six.

2. Literature Review

The issue of innovation has found various ways of connecting with a territory over the past 30 years. The first theorisation of this relationship is detected in the concept of the industrial district of the Third Italy (Bagnasco, 1977) in the late 1970s. This paradigm has been spread through the concept of an industrial cluster (Porter, 1990), which means a "geographical concentration of industries that take performance advantages through co-location, which refers to agglomeration economies, both of scale or scope". Further developments are traceable in science and technology parks (400 cases in Europe alone) and in the so-called technopolis. In all of these cases, the mechanism that generates innovation is mainly due to three factors:

1) the concentration of many and diverse areas of expertise in various fields of knowledge and production;
2) networks of cooperation among members;
3) the presence of catalysts that facilitate the combination of different skills and units.

In the 1990s the technological paradigm of districts is replaced by the National Innovation System (Lundvall, 1992 and Nelson, 1992), which focuses on macroeconomic factors as the basis for the process of spreading technology within society. However, in the late 1990s, some studies focused on local dimensions, such as learning regions, regional innovation system and local innovation systems (Cooke et al., 2004), characterised by:

- the ability of companies to learn and generate knowledge;
- organisational learning that is able to amplify the knowledge produced by individuals;
- systemic innovation (relative to an entire city-region) rather than linear innovation (internal research laboratories);

- institutions that work as switches selecting (on) or rejecting (off) innovations;
- development of social capital.

In this context, the awareness that innovation processes, i.e., the application of knowledge, have been implemented at the local level has grown in recent years, although the production of new knowledge is available on a global scale. Indeed, only in a restricted territorial area are collaborations among individuals more effective. These innovation processes lead to the creation, hybridisation, and spread of knowledge and technology from the world of scientific research to production and service sectors.

Since 1994, the key concepts of the learning region paradigm have been adopted by the European Commission, which issues a new family of strategic innovation and technological policies at the regional level: regional innovation and technology transfer strategies and infrastructures (RITTS), regional technology plans (RTP), regional innovation strategies (RIS) and regional programmes of innovative actions (PRIA).

After 2000, due to the gradual de-materialisation of the infrastructure, the progressive digitisation of innovation, the new forms of online learning and the advent of ever more virtual technologies a new approach has emerged linking regional innovation to society's knowledge and information management, the so-called intelligence region. This area is characterised by the presence of innovation systems combined with IT infrastructures and services of digital innovation. In this context, the model of the triple helix (Etzkowitz and Lydesdorff, 2000) and the model of the three Ts - technology, talent and tolerance (Florida, 2002) - have been developed. The first approach identifies the university-industry-government relationship as a complex of interdependent institutional spheres that overlap and complement each other along the process that leads to innovation. The second model shows that a good supply of technology and talented people is not enough for innovation and growth without being combined with a significant amount of tolerance (the social cohesion). These models have been developed with several other contributions mainly focusing on the role of creativity in urban contexts (among others Gabe, 2006; Markusen, 2006; and Fusco Girard et al., 2009).

The concept of intelligent or smart cities is grounded and rooted in these assumptions. In the early contributions in which this concept is explained (Shapiro, 2003, 2006, Glaeser, 2005; Glaeser and Berry, 2006), the emphasis is mainly on the role of human capital (thus in the metaphorical sense on creativity and intelligence) as the engine of growth and development.

In particular, Shapiro (2003) finds a positive correlation between human capital and employment growth for the period 1940 to 1990 in U.S. metropolitan areas. One explanation of this relationship may be the presence of omitted variables, i.e., variables not explicitly considered but correlated with both human capital and employment growth. Shapiro concludes that a highly educated population generates high levels of productivity and further growth through knowledge spillovers. Moreover, in areas inhabited by people with a high level of education, there is a rapid increase in the quality of life. Through the use of instrumental variables, it is also demonstrated that this relationship is significant if, as a proxy for human capital, a concentration of university graduates is used.

Similarly, Glaeser (2005), focusing primarily on U.S. cities, states that the highest rates of urban growth are present where a highly educated workforce is available. In particular, one of the mechanisms identified by this model is based on the assumption that innovation processes are promoted by entrepreneurs in sectors that require a highly skilled and educated workforce. Finally, high levels of human capital are also associated with a reduction in corruption and improvements in governance and performance.

In a subsequent study, Glaeser and Redlick (2008) not only introduce the concept of human capital but also the social capital assumption as a key hypothesis of urban growth. Accordingly, social capital should be encouraged through a series of local activities (political activism and activities such as group membership). Two desirable dynamics are considered. The first highlights that, in the case of a scarce investment in social capital, the region could become less attractive and therefore inhabitants could be compelled to relocate. The second considers the presence of a virtuous circle. Residents who choose to stay and live in a specific city could invest in social capital, improve the quality of life, and thereby make the city more attractive. This hypothesis could justify the intervention of government to use the subsidy instrument for the declining areas or cities with the aim to increase the livability and to change the circle from negative to virtuous.

The first operational definition of a smart city was proffered by Giffinger et al. (2007):

> "*A smart city is a city well performing in six characteristics, built on the 'smart' combination of endowments and activities of self-decisive, independent and aware citizens*"

This definition extends previous results by identifying six dimensions or characteristics: economics, people, governance, mobility, environment and quality of life. They, in turn, are broken down into 31 major factors and 74 indicators. This definition has allowed, for the first time, a classification of cities according to their level of smartness. This classification has become an important benchmark in the debate on smart cities, even if, by Giffinger and Haindlmaier (2010)'s own admission, it presents a number of limitations. For example, it is not possible to assess all of the indicators at a city level as a significant number of indicators (approximately 35%) are available only at the national level.

Following this approach, a recent study by Caragliu, Del Bo and Nijkamp (2009) includes in the definition of smart cities the following key concepts:

- the use of interconnected infrastructures to improve economic and political efficiency facilitating, at the same time, the development of social, cultural and urban development;
- the ability to be business-friendly to attract and accommodate business projects;
- a focus on social inclusion;

- the coexistence and complementarity of high-tech and soft infrastructure;
- a focus on the role of social and relational capital within the urban area;
- the sustainability of the environment.

The study, using a dataset derived from the Urban Audit, measures the effect of some variables that are essential to urban growth and uses the city's GDP as a proxy for the wealth of a city. The analysis confirms the existence of a positive correlation between urban welfare and the percentage of people employed in the creative sector[1], measures of public transport system, accessibility to services, level of e-government and, finally, quality of human capital.

The studies of Nijkamp et al. (2011) and Caragliu et al. (2009), which focus on the interrelationships among the components of smart cities as defined by Giffinger et al. (2007) and including human and social relations, link intellectual capital, health and governance concepts using an approach based on the triple helix model. In this framework, the city is called "smart" when:

"*Investments in human and social capital and traditional (transport) and modern (ICT) communication infrastructure fuel sustainable economic growth and a high quality of life, with a wise management of natural resources, through participatory governance*" (Caragliu et al., 2009, p.6). "*Furthermore, cities can become "smart" if universities and industry support government's investment in the development of such infrastructures*" (Nijkamp et al., 2011, p.3).

From another perspective, assuming the target is social innovation, smart cities are cities that create the necessary conditions of governance, infrastructure and technology to produce social innovation (Kanter and Litow, 2009). In other words, smart cities can solve social problems related to growth, to inclusion and to quality of life by listening and by involving various local actors including citizens, businesses and associations.

[1] A "creative" sector means the workforce is employed in sciences, engineering, education, information technology, research, arts and design.

When raw materials become information and knowledge, cities can be defined according to the way information and knowledge are produced, collected and shared with the aim of raising the process of innovation. Regardless of the type of communication (financial, economic, social or cultural), cities are increasingly active nodes of these intangible flows in addition to the physical flows (Dirks and Keeling, 2009).

Numerous scholars have tried to bring order to the heterogeneous definitions of the concept and to achieve a shared vision of a smart city. From this perspective, and depending on the priority given to different forms of communication and participation, some models of smart cities have been identified:

- **net cities** (Castells 2004): flexible cities able to relate to their populations and to the international flows (linked to the areas of finance, economy and culture), thus serving as a key connection between local and global actors;
- **open cities** (Partridge, 2004): cities that prioritise the transparency of their work through online publication of all acts, live broadcast streaming of council meetings, access to official acts, adoption of open data model, crowdsourcing, etc.;
- **sentient cities** (Shepard, 2011; Meeus et al., 2010): cities aimed primarily at improving operational efficiency and sustainable development through infrastructure that is able to produce and manage information regarding its operations it works and actively involve citizens in the priority areas of its functions (e.g., mobility, energy, quality of environment);
- **wiki cities** (Calabrese et al., 2009): cities whose inhabitants are well-informed (through real time location-sensitive tools) and can thus base their actions and decisions on good information, thus leading to overall increased efficiency and sustainability of the city environment.

- **cities 2.0** (Chadwick, 2009): cities that have as a fundamental characteristic the involvement of citizens (e-democracy, public contest, wikis government, co-design of services) in the management of public affairs;
- **neo-bohème cities** (Lloyd, 2006): cities that offer scope of bottom-up communication in the form of artistic production, thus creating the conditions for the re-development of urban areas;
- **creative cities** (Florida, 2002; Rios, 2008; Holland, 2008): cities whose objective is to mobilise and develop human resources and skills designed for global competition, thus cities must be tolerant and able to attract creative human capital to innovative and research fields;
- **resilient cities** (Otto-Zimmermann, 2011): cities that help citizens to better understand the risks of their own territory, especially related to climate change, through education and awareness, and they share information in the event of threatening events;
- **cloud cities** (Ballon et al., 2011; Washburn et al., 2010): cities that consider technology to be a facilitator of interaction and a software to connect ideas, initiatives, skills and experiences.

Accordingly, the features describing a smart city are complex and combine a host of factors. Because a shared definition of a smart city has not already been developed and promoted in the extant literature, for the purposes of this paper, we refer to the definition and measurement as given by Giffinger et al. (2007), while fully recognising the limitations of this approach.

3. The Methodology

As we have already emphasised, cities, as well as countries, must face the challenge of simultaneously combining competitiveness and sustainable urban development. In other words, cities must become efficient. According to the neoclassical economic theory, two agents having the same information on production function could maximise their profits and thus be efficient in an identical way. We apply the same hypothesis to those cities that have been defined as smart based on the analysis of Giffinger et al. (2007).

In reality, however, two cities – even if identical in terms of costs and profits – can produce only a similar output. In other words, the difference between the two cities can be explained through the analysis of efficiency and some unforeseen exogenous shocks, as described by Desli et al. (2002).

Traditionally, the empirical analysis of production functions has focused on the standard econometric approach based on the OLS model that incorporates a random error term that can take both positive and negative values (Thomas, 1993). However, the estimation of these production functions has certain limits. The main limitation is based on the fact that results represent an average relationship between output and inputs in particular sample data (Alaudddin et al., 1993).

Thus, a simple OLS regression is not sufficient for estimating the relationship between output and inputs, as described in Feld et al. (2004). Other relevant limits include the impossibility to discriminate between rent extraction and productive efficiency and to measure the distance of each unit of analysis from the efficiency frontier for a given production function.

Consequently, in recent years, several new econometric techniques have been developed to estimate the frontier of the production function to correspond to the economist's theoretical definition (Kalirajan and Shand, 1999).

To estimate a frontier production function, parametric or nonparametric techniques can be undertaken (Coelli et al., 1998). In this paper, we have estimated the production function of cities using the stochastic frontier approach (SFA) [2] initially and independently developed by Aigner et al. (1977) and Meeusen and van den Broeck (1977).

This approach allows us to distinguish between production inputs and efficiency/inefficiency factors and to disentangle distances from the efficient frontier between those due to systematic

[2] A number of comprehensive reviews of this literature are now available. See, for example, Forsund et al. (1980), Schmidt (1986), Bauer (1990), Greene (1993) and Coelli et al. (1998).

components and those due to noise. This parametric approach is preferred over a nonparametric approach as it avoids the outliers that are considered very efficient cities (Signorini, 2000).

The main idea is that the SFA, which represents the maximum output level for a given input set, is assumed to be stochastic to capture exogenous shocks beyond the control of cities.

Because all cities are not able to produce the same frontier output, an additional error term is introduced to represent technical inefficiency[3]. After these early studies, the SFA methodology was extended in many directions using both cross-sectional and panel data. The availability of panel data facilitates the study of the behaviour of technical inefficiency not only among units but even over time. Among others, Pitt and Lee (1981), Schmidt and Sickles (1984) Kumbhakar (1987) and Battese et al. (1989) have treated technical inefficiency as time invariant, while, for example, Cornwell et al., (1990), Kumbhakar (1990), Battese and Coelli (1992) and Lee and Schmidt (1993) have allowed technical inefficiency to vary over time even if they have modelled efficiency as a systematic function of time.

The search for the determinants of efficiency changes initially involved adopting a two stage approach in which the efficiencies estimated in the first stage were regressed against a vector of explanatory variables. Further development of this technique led to the adoption of a single stage approach in which explanatory variables were incorporated directly into the inefficiency error component[4]. In particular, Kumbhakar, Gosh and McGuckin (1991), noting the inconsistency between the independent and identically distributed (i.i.d.) assumption on the inefficiency effects in the first stage and the non-identical distribution of the predicted inefficiency effects in the second

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[3] We follow the Farrel (1957) measure of a firm's efficiency consisting of two components: technical and allocative. The former reflects the ability of a firm to obtain maximal output from a given set of inputs, while the latter reflects the ability of a firm to use the inputs in optimal proportions given their respective prices. These considerations are obviously true also at the country level considering that the aggregate output comes from the sum of national producers.

[4] For a review, see Kumbhakar and Knox - Lovell (2000).

stage, proposed a model in which the inefficiency effects were explicit functions of a vector of firm-specific factors and the parameters were estimated in a single-stage maximum likelihood procedure.

A further development of this first approach is the Battese and Coelli (1995) model in which the allocative efficiency is imposed, the first-order profit maximising conditions removed, and panel data are permitted. Thus, the Battese and Coelli (1995) specification may be expressed as:

$$Y_{it} = x_{it}\beta + (v_{it} - u_{it}) \qquad i=1,...,N,\ t=1,...,T \qquad (1)$$

where Y_{it} is (the logarithm of) the production of the *i-th* city in the *t-th* time period; x_{it} is a $k\times1$ vector of (transformations of the) input quantities of the *i-th* city in the *t-th* time period; β is a vector of unknown parameters. The unobserved random noise is divided into a first component v_{it}, which are random variables following the assumption of normally distributed error terms [iid $N(0, \sigma_V^2)$], and a second independent component defined as u_{it}, which are non-negative random variables. These variables are assumed to capture the effects of technical inefficiency in production and are assumed to be independently distributed as truncations at zero of the $N(m_{it}, \sigma_U^2)$ distribution.

The mean of this truncated normal distribution is a function of systematic variables that can influence the efficiency of a city:

$$m_{it} = z_{it}\delta + \varepsilon_{it}, \qquad (2)$$

where z_{it} is a $p\times1$ vector of variables that may have an effect on the production function of a city and δ is a $1\times p$ vector of parameters to be estimated.

Following Battese and Corra (1977), the simultaneous maximum likelihood estimation of the two equation system is expressed in terms of the variance parameters $\sigma^2=\sigma^2_v+\sigma^2_u$ and $\gamma=\sigma^2_u/(\sigma^2_v+\sigma^2_u)$ to provide asymptotically efficient estimates[5]. Hence, it is clear that the test on the significance of the parameter γ is a test on the significance of the stochastic frontier specification where the acceptance of the null hypothesis that the true value of the parameter equals zero implies that σ^2_u, the non-random component of the production function residual, is zero.

The technical efficiency of the *i-th* city in the *t-th* time period is given by:

$$TE_i=e^{(-u_i)}=e^{(-z_{it}\delta-\varepsilon_{it})} \tag{3}$$

4. Our Empirical Model

In this paper, we analyse the economic performance and the efficiency of several European cities following the 1995 Battese and Coelli' specification and using an unbalanced panel dataset. Model results are computed using the program FRONTIER 4.1, which can manage either balanced or unbalanced panel data.

Data for this study have been obtained from the Urban Audit dataset of EUROSTAT. The Urban Audit data provides information and comparable measurements on the different aspects of the quality of urban life in European cities. The analysis of life quality in a city is becoming a crucial aspect in the development of an area and, more generally, of a country. To attract and hold a skilled workforce, businesses, students, tourists and, most of all, residents, a city should be efficient or, in other words, smart.

Unfortunately, the Urban Audit dataset presents several limitations. In particular, data are collected every three years and many variables have missing data. Keeping in mind these

[5] The log-likelihood function and the derivatives are presented in the Appendix of Battese and Coelli (1993).

limitations of the data, we perform estimations using an unbalanced panel data of European cities in three different waves of the survey.

Our dataset has been selected based on the same 70 European cities considered in the ranking developed by Giffinger et al. (2007) (see Table in Appendix). Within the Urban Audit dataset, there are several waves of the survey[6]. However, due to comparability and missing data, we use only three out of the six waves: 1999-2002, 2003-2006 and 2007-2009.

In our model, the production of each city is measured by the gross domestic product[7] (Y_{it}) and, as usual, is assumed to be a function of three inputs: physical (K_{it}) and human (H_{it}) capital and labour (L_{it}). Because a city is not a firm, considering and assessing the physical capital of a city is challenging. As a first attempt, we consider two different aspects: houses measured by the number of dwellings and transport measured by the length of the public transport network (km)[8]. The second input, labour variable, is represented by the number of employees. As regards the third input, human capital, we consider the number of residents (aged 15-64) with ISCED level 3 or 4 - the highest level of education - as a proxy of the level of education of the labour force.

By assuming that the production function takes the log - linear Cobb-Douglas form, our stochastic frontier production model is specified as follows:

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[6] The first three waves of the survey (1989-1993, 1994-1998, 1999-2002) can be considered as a “pilot”, as the first full-scale European Urban Audit took place in 2003 for the then 15 countries of the European Union. In 2004, the project was extended to the 10 new member states plus Bulgaria, Romania and Turkey (25 EU countries). For the 2003/2004 data collection exercise, 336 variables were collected, covering most aspects of urban life. The second full-scale data collection for the Urban Audit started in 2006 and was completed in 2007. It involved 321 European cities in the 27 countries of the European Union along with 36 additional cities in Norway, Switzerland and Turkey. The basic philosophy was to deviate as little as possible from the concepts used in the 2003/2004 collection. However, in some cases, changes were made with the aim of improving comparability, data availability and quality. In the last two waves, 2007-2009 and 2010-2012, small changes were made to the lists of variables and cities compared to 2006.

[7] We have been obliged to use the proxy “GDP in PPS of NUTS 3 region ‘because of a lack of data of the gross domestic product of city/region/country’ variable in the Urban Audit dataset

[8] Because in the very recent literature on smart cities nobody has tried to analyse the production function and its components at the city level, it has been difficult to find an accepted measure of physical capital of a city. A first attempt to measure this input was conducted by the Economist Intelligence Unit (2012). Even if we are aware that this report is not an academic one, it is the only available at the moment near to our assumption of city’s physical capital.

$$ln(Y/L)_{it} = \beta_0 + \beta_1 ln(Kdwelling/L)_{it} + \beta_1 ln(Ktransport_{net}/L)_{it} + \beta_2 ln(H/L)_{it} + v_{it} - u_{it} \quad (4)$$

where the dependent variable is the value of the economic performance of the *i-th* city at time *t* (*i=1,...,N; t=1,...,T*) divided by a scale variable (the labour force) to remove potential problems of heteroskedasticity, multicollinearity and output measurement (Hay-Liu, 1997). The independent variables are i) per-capita physical capital (*Kdwelling/L* and *Ktransport_net/L*), which represents the city capital stock per worker of the *i-th* city at time *t*, and ii) human capital (*H/L*), which is the city education level of residential people per worker of the *i-th* city at time *t*.

According to the SFA, the systematic component of error includes all the factors that can influence the efficiency of the phenomenon analysed. In our model, we consider Giffinger et al (2007) indictors as explanatory variables of the second component of the error, as shown in the following equation:

$$\begin{aligned} u_{it} = \gamma_0 + \gamma_1 Smart_{Economy_{it}} + \gamma_2 Smart_{People_{it}} + \gamma_3 Smart_{Governance_{it}} + \gamma_4 Smart_{Mobility_{it}} \\ + \gamma_5 Smart_{Environment_{it}} + \gamma_6 Smart_{Living_{it}} + \sum_{k=7}^{26} \gamma_k Countrydummy + \varepsilon_{it} \end{aligned} \quad (5)$$

where $Smart\_Economy_{it}$, $Smart\_People_{it}$, $Smart\_Governance_{it}$, $Smart\_Mobility_{it}$, $Smart\_Environment_{it}$ and $Smart\_Living_{it}$ represent the indicators that jointly describe the factors of a smart city, as described by Giffinger et al. (2007). In Giffinger's analysis, the group of researchers has developed six indicators on the basis of which they have ranked 70 European medium-sized cities. As previously described herein, we are aware of the limitations of the Giffinger et al. (2007) analysis. In particular, we are critical of the use of certain data at the national level, even if it is useful to broaden the database, and we do not agree with the mix of timing of the different factors on the basis of the six indicators. Moreover, the methodology to aggregate factors of the six indicators is too simple[9], and it does not consider the differences among cities. However, this approach represents, until now, the most relevant benchmark for smartness of cities within the European Union. As previously discussed, the focus of our analysis is the impact of smart city indicators on the performances of European cities by measuring the efficiency of a city to attract a high skilled labour force, high technology businesses, and the best students and to– thus be an efficient city.

Finally, to analyse a recent issue that emerged in the new economic geography literature that asserts that a city belonging to a well-developed area can perform better than a city belonging to a less developed area, we have introduced m-1 country dummies to capture the influence of city geographical localisation. A country in northern Europe should influence positively the city's economic performance, and thus, the technical inefficiency should be less with respect to others. In other words, the gap from the stochastic frontier of this city should not be very large.

5. Descriptive Evidence and Empirical Results

Table 1 provides the basic descriptive statistics for estimating the efficiency of European cities. In particular, it describes output and input variables used in the analysis, subdividing cities according to the country to which the city belongs. The descriptive statistics are reported only for the unbalanced dataset (models 1 and 2 of the SFA estimations), where the considered cities are reduced to 54 cities. In the Appendix, we show the differences, in terms of cities considered, among our estimation datasets (54 cities for models 1 and 2 and 39 cities for models 3 and 4), the Urban Audit dataset and the Giffinger et al. (2007) dataset. These differences are the main consequence of the missing value problem. We observe that only Germany is considered as it has 6 cities in the

[9] The aggregate additivity of the factors divided by the number of values added.

sample, while the other countries have less and some present with only one city. Moreover, it is clear that the length of the public transport network per worker has extremely low values and a huge missing data problem. For this reason, when, in our estimation (models 3 and 4), we introduce this variable, cities undergoes a change, decreasing to 39.

As regards the smart indicators, we note that the Scandinavian cities are highly ranked, while Germany and the United Kingdom are, more or less, in the middle of the classification, a situation described in more detail in the study by Giffinger et al. (2007).

Table 1: Descriptive statistics

		Y_L	K_dwel_L	K_transp_L	H_L	SE	SP	SG	SM	SEn	SL
BG	**mean**	16,490	1.23	0.004	1.07	52.00	69.50	69.50	64.00	63.00	68.50
	p50	16,700	1.22	0.01	1.07	52.00	69.50	69.50	64.00	63.00	68.50
	sd	2,295	0.10	0.002	0.09	1.15	0.58	0.58	5.77	6.93	0.58
	min	13,970	1.12	0.002	1.01	51.00	69.00	69.00	59.00	57.00	68.00
	max	18,591	1.35	0.01	1.14	53.00	70.00	70.00	69.00	69.00	69.00
	N	4	4	3	2	4	4	4	4	4	4
CZ	**mean**	23,730	0.86	0.002		48.50	50.00	58.00	26.50	54.50	32.00
	p50	23,730	0.86	0.002		48.50	50.00	58.00	26.50	54.50	32.00
	sd	3,586	0.03			7.78	1.41	4.24	4.95	0.71	5.66
	min	21,194	0.84	0.002		43.00	49.00	55.00	23.00	54.00	28.00
	max	26,266	0.88	0.002		54.00	51.00	61.00	30.00	55.00	36.00
	N	2	2	1	0	2	2	2	2	2	2
DE	**mean**	58,722	1.04	0.002	0.67	28.47	43.88	28.82	15.53	22.41	34.88
	p50	56,903	0.94	0.002	0.62	32.00	45.00	27.00	16.00	21.00	38.00
	sd	22,413	0.56	0.001	0.39	15.42	4.91	10.77	4.32	7.87	7.61
	min	39,213	0.64	0.001	0.37	9.00	34.00	19.00	10.00	15.00	22.00
	max	135,669	3.12	0.004	2.10	47.00	50.00	48.00	22.00	38.00	45.00
	N	17	17	17	17	17	17	17	17	17	17
DK	**mean**	42,980	0.86	0.01	0.60	12.00	2.67	5.00	8.33	32.00	13.33
	p50	42,411	0.88	0.01	0.60	15.00	3.00	5.00	9.00	26.00	12.00

	sd	2,064	0.06		0.03	7.00	1.53	1.00	3.06	15.87	3.21
	min	41,261	0.79	0.01	0.56	4.00	1.00	4.00	5.00	20.00	11.00
	max	45,269	0.90	0.01	0.62	17.00	4.00	6.00	11.00	50.00	17.00
	N	3	3	1	3	3	3	3	3	3	3
EE	**mean**	16,799	0.85	0.003	0.69	40.00	15.00	30.00	47.00	49.00	60.00
	p50	16,030	0.83	0.002	0.65	40.00	15.00	30.00	47.00	49.00	60.00
	sd	3,184	0.09	0.003	0.19	0.00	0.00	0.00	0.00	0.00	0.00
	min	14,069	0.77	0.002	0.53	40.00	15.00	30.00	47.00	49.00	60.00
	max	20,296	0.94	0.01	0.90	40.00	15.00	30.00	47.00	49.00	60.00
	N	3	3	3	3	3	3	3	3	3	3
ES	**mean**	59,996	1.24	0.003	0.55	35.88	52.50	36.75	49.50	42.50	40.25
	p50	58,832	1.27	0.003	0.56	37.00	53.00	38.00	51.00	32.00	41.00
	sd	6,847	0.16	0.001	0.05	9.16	2.93	2.31	4.72	21.37	5.57
	min	48,843	0.96	0.002	0.47	22.00	48.00	34.00	44.00	24.00	34.00
	max	67,557	1.42	0.003	0.62	44.00	55.00	39.00	54.00	68.00	46.00
	N	8	8	2	6	8	8	8	8	8	8
FI	**mean**	48,508	1.12	0.01	0.63	22.86	7.29	1.71	24.57	11.86	10.00
	p50	49,068	1.12	0.004	0.62	25.00	7.00	2.00	27.00	12.00	9.00
	sd	4,313	0.05	0.004	0.02	6.57	0.76	0.76	3.36	1.07	4.00
	min	42,586	1.05	0.004	0.60	16.00	6.00	1.00	21.00	11.00	8.00
	max	55,202	1.18	0.01	0.65	29.00	8.00	3.00	28.00	14.00	19.00
	N	7	7	5	7	7	7	7	7	7	7
FR	**mean**	46,132	1.13	0.003		38.00	30.60	26.40	27.40	7.00	20.60
	p50	44,111	1.03	0.003		38.00	31.00	26.00	26.00	8.00	20.00
	sd	6,528	0.22	0.001		7.04	5.18	4.39	3.65	3.54	5.32
	min	38,034	1.00	0.002		30.00	23.00	22.00	24.00	1.00	15.00
	max	53,768	1.52	0.005		48.00	37.00	33.00	33.00	10.00	27.00
	N	5	5	5	0	5	5	5	5	5	5
HU	**mean**	21,798	1.03	0.004	1.00	57.00	64.50	66.00	54.00	67.50	55.50
	p50	22,067	1.03	0.002	1.00	57.00	64.50	66.00	54.00	67.50	55.50
	sd	1,611	0.04	0.003	0.05	1.15	2.89	1.15	4.62	2.89	2.89
	min	19,743	1.00	0.002	0.95	56.00	62.00	65.00	50.00	65.00	53.00
	ma	23,31	1.07	0.01	1.06	58.00	67.0	67.0	58.0	70.0	58.0

	x	4					0	0	0	0	0
	N	4	4	4	4	4	4	4	4	4	4
IE	mean	85,942	1.02		0.74	2.00	26.00	25.00	45.00	66.00	21.00
	p50	85,942	1.02		0.74	2.00	26.00	25.00	45.00	66.00	21.00
	sd										
	min	85,942	1.02		0.74	2.00	26.00	25.00	45.00	66.00	21.00
	max	85,942	1.02		0.74	2.00	26.00	25.00	45.00	66.00	21.00
	N	1	1	0	1	1	1	1	1	1	1
LT	mean	22,084	0.91		0.94	55.00	36.00	66.00	55.00	27.00	65.00
	p50	22,084	0.91		0.94	55.00	36.00	66.00	55.00	27.00	65.00
	sd	2,626	0.06		0.08	0.00	0.00	0.00	0.00	0.00	0.00
	min	20,227	0.87		0.88	55.00	36.00	66.00	55.00	27.00	65.00
	max	23,941	0.95		0.99	55.00	36.00	66.00	55.00	27.00	65.00
	N	2	2	0	2	2	2	2	2	2	2
LU	mean	29,066	0.29	0.001	0.09	1.00	2.00	13.00	6.00	25.00	6.00
	p50	29,066	0.29	0.001	0.09	1.00	2.00	13.00	6.00	25.00	6.00
	sd										
	min	29,066	0.29	0.001	0.09	1.00	2.00	13.00	6.00	25.00	6.00
	max	29,066	0.29	0.001	0.09	1.00	2.00	13.00	6.00	25.00	6.00
	N	1	1	1	1	1	1	1	1	1	1
LV	mean	20,985	1.09	0.01		60.00	12.00	63.00	61.00	61.00	70.00
	p50	20,612	1.07	0.01		60.00	12.00	63.00	61.00	61.00	70.00
	sd	1,871	0.05	0.004		0.00	0.00	0.00	0.00	0.00	0.00
	min	19,328	1.05	0.004		60.00	12.00	63.00	61.00	61.00	70.00
	max	23,014	1.16	0.01		60.00	12.00	63.00	61.00	61.00	70.00
	N	3	3	2	0	3	3	3	3	3	3
NL	mean	50,406	0.87	0.003	0.50	18.75	13.25	15.75	7.25	40.50	19.50
	p50	47,685	0.84	0.002	0.47	19.00	13.50	15.50	3.50	38.00	20.50
	sd	10,059	0.14	0.002	0.12	11.00	3.30	1.71	8.54	7.19	5.07
	min	41,960	0.73	0.002	0.39	6.00	9.00	14.00	2.00	35.00	13.00
	max	64,294	1.06	0.005	0.66	31.00	17.00	18.00	20.00	51.00	24.00
	N	4	4	3	4	4	4	4	4	4	4
PL	mean	29,971	1.07	0.002	1.33	66.40	35.20	56.60	48.60	55.20	55.20

	p50	32,809	1.12	0.002	1.36	67.00	27.00	57.00	46.00	56.00	55.00
	sd	11,307	0.27	0.0004	0.30	2.41	17.46	2.30	7.44	5.89	3.96
	min	14,932	0.65	0.001	0.86	63.00	19.00	53.00	41.00	47.00	50.00
	max	44,179	1.40	0.002	1.68	69.00	56.00	59.00	57.00	62.00	61.00
	N	5	5	5	5	5	5	5	5	5	5
PT	**mean**	32,308	0.95	0.01	0.32	52.00	63.00	54.00	49.00	16.00	37.00
	p50	32,308	0.95	0.01	0.32	52.00	63.00	54.00	49.00	16.00	37.00
	sd										
	min	32,308	0.95	0.01	0.32	52.00	63.00	54.00	49.00	16.00	37.00
	max	32,308	0.95	0.01	0.32	52.00	63.00	54.00	49.00	16.00	37.00
	N	1	1	1	1	1	1	1	1	1	1
RO	**mean**	19,372	1.19			53.50	64.50	62.00	63.00	8.50	60.50
	p50	19,372	1.19			53.50	64.50	62.00	63.00	8.50	60.50
	sd	4,380	0.18			4.95	0.71	2.83	1.41	6.36	2.12
	min	16,276	1.07			50.00	64.00	60.00	62.00	4.00	59.00
	max	22,469	1.32			57.00	65.00	64.00	64.00	13.00	62.00
	N	2	2	0	0	2	2	2	2	2	2
SE	**mean**	49,115	0.97	0.01	0.69	37.20	8.00	8.20	34.80	31.60	19.60
	p50	48,994	0.99	0.01	0.68	36.00	10.00	7.00	34.00	22.00	26.00
	sd	5,488	0.02		0.02	1.64	2.74	1.64	1.10	13.15	8.76
	min	41,914	0.94	0.01	0.66	36.00	5.00	7.00	34.00	22.00	10.00
	max	56,702	0.99	0.01	0.72	39.00	10.00	10.00	36.00	46.00	26.00
	N	5	5	1	5	5	5	5	5	5	5
SI	**mean**	35,066	0.75	0.002	0.74	28.50	16.00	40.00	35.50	2.50	30.50
	p50	34,146	0.74	0.002	0.74	28.50	16.00	40.00	35.50	2.50	30.50
	sd	5,901	0.12	0.001	0.14	22.46	5.48	3.29	4.93	0.55	1.64
	min	26,983	0.60	0.001	0.62	8.00	11.00	37.00	31.00	2.00	29.00
	max	42,326	0.88	0.003	0.87	49.00	21.00	43.00	40.00	3.00	32.00
	N	6	6	6	4	6	6	6	6	6	6
SK	**mean**	21,927	0.76	0.004	0.97	66.00	43.33	51.00	51.00	43.33	47.67
	p50	23,155	0.76	0.003	0.95	66.00	43.00	51.00	52.00	53.00	47.00
	sd	2,907	0.08	0.003	0.12	3.46	2.18	0.87	2.29	18.38	3.50

	min	16,559	0.66	0.001	0.84	62.00	41.00	50.00	48.00	19.00	44.00
	max	25,529	0.88	0.01	1.16	70.00	46.00	52.00	53.00	58.00	52.00
	N	9	9	9	5	9	9	9	9	9	9
UK	**mean**	54,588	0.78		0.45	7.00	37.22	46.22	35.89	63.89	38.78
	p50	52,841	0.78		0.38	7.00	38.00	47.00	35.00	64.00	40.00
	sd	5,030	0.07		0.13	3.57	5.52	2.86	3.98	2.15	4.52
	min	49,483	0.68		0.35	3.00	28.00	42.00	32.00	60.00	30.00
	max	66,110	0.92		0.71	13.00	42.00	49.00	42.00	67.00	43.00
	N	9	9	0	7	9	9	9	9	9	9

In Table 2, we report the results of the stochastic frontier estimations. Because, in all specifications, we reject the null hypothesis of the insignificance of the non-negative error component (γ), we conclude that the stochastic frontier specification is a good model to analyse the effect of smart city indicators on cities' economic performances. Moreover, the parameter (γ) also indicates the proportion of the total variance in the model that is accounted for by the inefficiency effects. This parameter, which is significant at the 1% level in all estimations, varies between 0.48 and 0.80, thus indicating that 48% to 80% of the variance is explained by the inefficiency effects, confirming that the inefficiency effects are important in explaining the total variance in the model.

In particular, in the first and second columns, we report the results of estimations, which exclude the length of the transport net but include the country dummies (column 2), In the third and fourth columns, however, the length of the transport net is included, and thus, the missing value problem drastically reduces the observations.

In all columns, the results indicate that production function performs quite well because physical capital measured by dwellings shows always a positive and significant sign, while human capital and the length of the transport net has negative, albeit insignificant, signs. These results should be explained with respect to the relevance of the missing data problem within the dataset as described by the number of observations.

However, the coefficients for human and physical capital are both significantly less than 1, thus indicating that output is inelastic with respect to both inputs. In addition, the sum of the inputs' coefficients is less than 1, which implies decreasing returns to scale.

When we observe the signs of the smart city indicators in the first column, we note that only Smart People and Smart Environment show a negative sign, thus indicating that both variables have a positive effect on efficiency and, hence, a negative impact on inefficiency. The other smart indicators show a vice versa effect in that they increase inefficiency and decrease efficiency. However, we must emphasise that the signs are not robust to the inclusion of other variables and that the significance of the coefficients is drastically reduced in the other columns of Table 2.

Table 2: Inefficiency models with GDP pro-capita as the dependent variable

dependent variable: gdp/L	**1**	**2**	**3**	**4**
Const β0	10.66***	10.82***	10.16***	10.58***
t	83.00	81.34	20.80	9.85
K dwelling/L β1	0.57***	0.51***	0.62***	0.51***
t	4.41	4.13	4.15	3.45
K_transport net/L β2			-0.11*	-0.13
t			-1.73	-1.31
H/L β3	-0.14**	-0.06	-0.08	0.16
t	-2.44	-1.06	-0.60	0.79
const γ0	-3.86***	-0.91	-3.98***	-2.22***
t	-11.13	-0.92	-5.85	-2.76
Smart Economy γ1	0.33***	0.44***	0.03	0.14
t	3.30	2.63	0.14	0.48
Smart People γ2	-0.21**	-0.17	-0.11	-0.07
t	-2.43	-0.71	-0.83	-0.16
Smart Governance γ3	0.36***	0.41	-0.07	0.21
t	2.64	1.37	-0.40	0.55
Smart Mobility γ4	0.47***	0.15	0.66***	0.58
t	3.89	0.45	3.67	1.52

Smart Environment γ5	-0.01	0.08	-0.01	-0.14
t	-0.24	0.58	-0.09	-0.57
Smart Living γ6	0.22	-0.33	0.70**	0.19
t	1.08	-1.02	1.96	0.30
CZ γ7		-0.65*		-0.23
t		-1.64		-0.27
DE γ8		-1.32***		-0.61
t		-3.29		-1.07
DK γ9		-0.16		-1.05
t		-0.31		-1.06
EE γ10		-0.05		-0.13
t		-0.14		-0.27
ES γ11		-1.18***		-2.92***
t		-2.82		-2.75
FI γ12		-0.12		0.07
t		-0.17		0.07
FR γ13		-0.87**		-0.72
t		-2.30		-1.08
HU γ14		-0.51**		-0.30
t		-2.40		-0.60
IE γ15		-0.64		
t		-0.76		
LT γ16		-0.54**		
t		-2.16		
LU γ17		0.03		-0.25
t		0.03		-0.25
LV γ18		-0.65		-0.44
t		-1.53		-0.47
NL γ19		-1.16		-0.07
t		-1.57		-0.07
PL γ20		-0.87***		-0.47
t		-3.96		-1.16
PT γ21		-0.86**		-2.26
t		-2.50		-1.59
RO γ22		-0.14		
t		-0.38		
SE γ23		-1.25***		-1.71
t		-2.66		-1.49
SI γ24		-0.69*		-1.08
t		-1.72		-1.28
SK γ25		-0.69***		-0.45
t		-3.57		-1.27
UK γ26		-1.29**		
t		-2.49		

Number of cities	54	54	39	39
Observations	101	101	69	69
Sigma squared	0.09***	0.04***	0.09***	0.06
t	4.76	3.09	3.75	1.57
Gamma	0.59***	0.48***	0.65***	0.80**
t	5.96	3.33	5.98	2.37
Log likelihood	-1.79	32.65	-1.35	9.28

*Note: * significant at 10%; ** significant at 5%; *** significant at 1%*

To deepen our analysis, we have estimated technical inefficiencies for each cit, using the model described in column (2) and shown in Table 3 and the model described in column (4) and shown in Table 4. In both tables, we report the technical inefficiencies of European cities for three separate years - 2000, 2004 and 2008 -which represent the three different waves of the survey. We then rank the European cities according to the level of inefficiency reached in 2004.

The results confirm that the inefficient cities are those belonging to the eastern European countries, but they do not confirm that the Scandinavian cities are the most efficient. In Table 3, in 2004, among the most efficient European cities, we find some German and United Kingdom cities. Different from Giffinger et al. (2007)'s analysis, a city belonging to a well-developed and best performing country can perform better than a city that belongs to a developing country and/or to a country that places less importance on economic and financial issues.

To better understand and emphasise the differences, we compare our European city rankings with that of Giffinger et al. (2007) (see Table 5). In particular, our comparison is based on the rankings resulting from model 4 for the year 2004 where only 36 cities are considered. The comparison highlights the gap, in the last column, between the resulting relative positions of the 36 cities. For 13 out of 36 cities, the gap is not relevant (less than 3 positions), thus suggesting that the two rankings provide similar results, while for the rest of the cities, the gap increases quickly, reaching a spread of 22 positions in the worst case (the city of Aalborg in Denmark).

Table 3: European city ranking of technical inefficiency based on 2004 for model 2

CITY	COUNTRY	2000	2004	2008
Pleven	BG		1	1
Ruse	BG		2	2
Tartu	EE	1	3	3
Liepaja	LV	3	4	4
Miskolc	HU	5	5	
Pecs	HU	6	6	
Kaunas	LT	7	7	
Banska Bystrica	SK	8	8	5
Nitra	SK	10	9	7
Kosice	SK	12	10	6
Maribor	SI	16	11	8
Aalborg	DK		12	
Odense	DK		13	
Oulu	FI		14	
Umeå	SE	22	15	
Tampere	FI	25	16	9
Oviedo	ES	26	17	11
Turku	FI	24	18	10
Aarhus	DK		19	
Ljubljana	SI	28	20	12
Valladolid	ES	32	21	13
Magdeburg	DE	30	22	18
Kiel	DE	33	23	14
Pamplona/Iruña	ES	34	24	
Enschede	NL		25	
Jönköping	SE	35	26	17
Groningen	NL		27	
Aberdeen	UK		28	16
Nijmegen	NL		29	
Erfurt	DE	36	30	19
Portsmouth	UK	37	31	20
Göttingen	DE		32	21
Eindhoven	NL		33	
Trier	DE	38	34	22
Leicester	UK	41	35	23
Regensburg	DE	40	36	24
Bialystok	PL	15		
Bydgoszcz	PL	17		
Cardiff	UK			15
Clermont-Ferrand	FR	27		
Coimbra	PT	18		
Cork	IE	39		
Dijon	FR	29		
Kielce	PL	14		
Luxembourg (city)	LU	31		
Montpellier	FR	23		
Nancy	FR	21		
Plzen	CZ	13		
Poitiers	FR	20		
Rzeszow	PL	9		
Sibiu	RO	2		
Szczecin	PL	19		
Timisoara	RO	4		
Usti nad Labem	CZ	11		

Table 4: European city ranking of technical inefficiency based on 2004 for model 4

CITY	COUNTRY	2000	2004	2008
Ruse	BG		1	2
Tartu	EE	2	2	3
Miskolc	HU	3	3	
Liepaja	LV		4	4
Banska Bystrica	SK	6	5	5
Nitra	SK	4	6	6
Pecs	HU	7	7	
Kosice	SK	9	8	7
Maribor	SI	12	9	8
Magdeburg	DE	14	10	14
Tampere	FI	20	11	9
Turku	FI	24	12	
Göttingen	DE		13	10
Erfurt	DE	21	14	12
Ljubljana	SI	19	15	11
Enschede	NL		16	
Kiel	DE	22	17	13
Nijmegen	NL		18	
Trier	DE	26	19	15
Eindhoven	NL		20	
Regensburg	DE	28	21	17
Valladolid	ES		22	
Aarhus	DK		23	
Bialystok	PL	8		
Bydgoszcz	PL	10		
Clermont-Ferrand	FR	17		
Coimbra	PT	25		
Dijon	FR	23		
Jönköping	SE			16
Kielce	PL	5		
Luxembourg (city)	LU	27		
Montpellier	FR	16		
Nancy	FR	18		
Oviedo	ES			18
Pleven	BG			1
Plzen	CZ	11		
Poitiers	FR	15		
Rzeszow	PL	1		
Szczecin	PL	13		

Table 5: Comparison between the two European city rankings

CITY	COUNTRY	VIENNA RANKING	2004 MODEL 4 RANKING	GAP
Liepaja	LV	33	33	0
Nijmegen	NL	8	8	0
Enschede	NL	12	12	0
Joenkoeping	SE	11	11	0
Ruse	BG	36	35	1
Pleven	BG	35	36	1
Pecs	HU	32	31	1
Kaunas	LT	31	30	1
Groningen	NL	9	10	1
Nitra	SK	27	28	1
Banska Bystrica	SK	30	29	1
Miskolc	HU	34	32	2
Kosice	SK	29	27	2
Eindhoven	NL	7	4	3
Magdeburg	DE	19	15	4
Kiel	DE	20	14	6
Ljubljana	SI	10	17	7
Goettingen	DE	13	5	8
Oviedo	ES	28	20	8
Umeaa	SE	14	22	8
Maribor	SI	17	26	9
Tartu	EE	24	34	10
Valladolid	ES	26	16	10
Erfurt	DE	18	7	11
Pamplona	ES	25	13	12
Trier	DE	16	3	13
Regensburg	DE	15	1	14
Aberdeen	UK	23	9	14
Tampere	FI	5	21	16
Portsmouth	UK	22	6	16
Aarhus	DK	1	18	17
Turku	FI	2	19	17
Oulu	FI	6	23	17
Leicester	UK	21	2	19
Odense	DK	4	24	20
Aalborg	DK	3	25	22

6. Conclusions

In this paper, we analysed how a number of European cities face the challenge of simultaneously combining competitiveness and sustainable urban development. We have focused our attention on the efficiency of the European cities studied by Giffinger et al. (2007).

Based on Giffinger et al. (2007)'s report, we select the same 70 European cities considered in the ranking of medium-sized cities. Using the six indicators that jointly describe a smart city, we analyse the economic performance and the efficiency of these European cities. Applying the stochastic frontier approach, we distinguish between production inputs and efficiency/inefficiency factors, and we disentangle distances from the efficient frontier ranking of the cities. Results confirm that production function performs quite well. Moreover, results show that only Smart-People and Smart-Environment have positive effects on efficiency, while the other smart indicators increase the city's inefficiency.

Finally, we rank the European cities according to the level of inefficiency reached in 2004, highlighting several differences with the study of Giffinger (2007). This allows us to compare different characteristics and to identify strengths and weaknesses of medium-sized cities. Among the most efficient European cities, we find some German and United Kingdom cities, while the inefficient cities are located in the eastern European countries. This implies that a city belonging to a well-developed, best performing country can perform better than a city that belongs to a developing country and/or to a country that places less importance on economic and financial issues.

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APPENDIX

Country	70 Cities By Giffinger et al. (2007)	69 Cities Collected By Urban Audit	54 Cities In Our Unbalanced Panel For Models 1 and 2	39 Cities In Our Unbalanced Panel For Models 3 and 4
AUSTRIA	Graz Innsbruck Linz Salzburg	Graz Innsbruck Linz Salzburg		
BELGIUM	Brugge Gent	Brugge Gent		
BULGARIA	Pleven Ruse	Pleven Ruse	Pleven Ruse	Pleven Ruse
CZECH REPUBLIC	Plzen Usti Nad Labem	Plzen Usti Nad Labem	Plzen Usti Nad Labem	Plzen Usti Nad Labem
GERMANY	Erfurt Goettingen Kiel Magdeburg Regensburg Trier	Erfurt Goettingen Kiel Magdeburg Regensburg Trier	Erfurt Goettingen Kiel Magdeburg Regensburg Trier	Erfurt Goettingen Kiel Magdeburg Regensburg Trier
DENMARK	Aalborg Aarhus Odense	Aalborg Aarhus Odense	Aalborg Aarhus Odense	Aarhus
ESTONIA	Tartu	Tartu	Tartu	Tartu
GREECE	Larisa Patrai	Larisa Patrai		
SPAIN	Oviedo Pamplona Valladolid	Oviedo Pamplona Valladolid	Oviedo Pamplona Valladolid	Oviedo Valladolid
FINLAND	Oulu Tampere Turku	Oulu Tampere Turku	Oulu Tampere Turku	Tampere Turku
FRANCE	Clermont-Ferrand Dijon Montpellier Nancy Poitiers	Clermont-Ferrand Dijon Montpellier Nancy Poitiers	Clermont-Ferrand Dijon Montpellier Nancy Poitiers	Clermont-Ferrand Dijon Montpellier Nancy Poitiers
CROATIA	Zagreb	Zagreb		

HUNGARY	Gyor Miskolc Pecs	Gyor Miskolc Pecs	Miskolc Pecs	Miskolc Pecs
IRELAND	Cork	Cork	Cork	
ITALY	Ancona Perugia Trento Trieste	Ancona Perugia Trento Trieste		
LATVIA	Kaunas	Kaunas	Kaunas	
LUXEMBOURG	Luxembourg	Luxembourg	Luxembourg	Luxembourg
LITHUANIA	Liepaja	Liepaja	Liepaja	Liepaja
NETHERLANDS	Eindhoven Enschede Groningen Maastricht Nijmegen	Eindhoven Enschede Groningen Nijmegen	Eindhoven Enschede Groningen Nijmegen	Eindhoven Enschede Nijmegen
POLAND	Bialystok Bydgoszcz Kielce Rzeszow Szczecin	Bialystok Bydgoszcz Kielce Rzeszow Szczecin	Bialystok Bydgoszcz Kielce Rzeszow Szczecin	Bialystok Bydgoszcz Kielce Rzeszow Szczecin
PORTUGAL	Coimbra	Coimbra	Coimbra	Coimbra
ROMANIA	Craiova Sibiu Timisoara	Craiova Sibiu Timisoara	Sibiu Timisoara	
SWEDEN	Joenkoeping Umeaa	Joenkoeping Umeaa	Joenkoeping Umeaa	Joenkoeping
SLOVENIA	Ljubljana Maribor	Ljubljana Maribor	Ljubljana Maribor	Ljubljana Maribor
SLOVAKIA	Banska Bystrica Kosice Nitra	Banska Bystrica Kosice Nitra	Banska Bystrica Kosice Nitra	Banska Bystrica Kosice Nitra
UNITED KINGDOM	Aberdeen Cardiff Leicester Portsmouth	Aberdeen Cardiff Leicester Portsmouth	Aberdeen Cardiff Leicester Portsmouth	