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SEARCHING FOR THE SOURCE OF TECHNICAL INEFFICIENCY OF ITALIAN JUDICIAL DISTRICTS. AN EMPIRICAL INVESTIGATION USING DEA DOUBLE BOOTSTRAPPING APPROACH

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Searching for the source of technical inefficiency of Italian Judicial Districts. An empirical investigation using DEA double bootstrapping approach

VERY PRELIMINARY DRAFT

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Abstract

The aim of this study is twofold. First, we investigate the efficiency levels of the activity of Italian judicial district on civil cases in 2006. For this purpose, we applied the Data Envelopment Analysis (DEA). Since DEA is an estimation procedure that relies on extreme points, it could be extremely sensitive to data selection, aggregation, model specification, and data errors we employ smoothed homogeneous bootstrap procedure to get more reliable efficiency rankings. Second, we analyse the determinants of the efficiency levels applying semi-parametric two-stage technique (Simar and Wilson 2007). This technique overcomes severe limitations inherent in using the two-stage DEA approach commonly employed in the efficiency literature.

JEL codes: D24, K41, K49

Keywords: civil courts efficiency, law enforcement, non-parametric methods

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I. INTRODUCTION

In the literature there has been an increasing interest toward the effects of the efficiency of judicial system on the economic development. Several problems may influence the access and citizen's equality before the law, the enforcement of laws and the guarantee of property rights and contracts such as congestion (Rosales-Lopez, 2008), the high cost and delay of procedures (Dalla Pellegrina, 2008), the lack of incentives to increase judges' productivity (Marchesi, 2007; Schneider, 2008). During the last decade in Italy, each government has reformed the judicial system with the aim to achieve a quicker, less costly and more efficient justice posing particular attention on civil cases. However, the proposed goal is still far from being reached. The general Attorney of court of cassation, in his 2008 report on the judicial system, describes the main weaknesses of Italian system. In particular, the main causes of malfunctioning of judicial system are the inappropriate distribution of judicial districts in Italy, the existence of extremely stiff and bureaucratic rules regulating the use of financial resources; the absence of any mechanism to filter the relevance and importance of litigations before reaching the court; finally, the increasing number of free riders who start a dispute only to postpone the fulfilment of legal obligation.

On the same line of research, Antonelli and Marchesi (1999) point out that the dimension of the geographical areas under the control of the majority of judicial district is sub-optimal leaving room for relevant economies of scale. In 1999, the dimension of 72% of judicial court was sub-optimal (less than 20 judges). Antonelli and Marchesi (1999), thus, suggest that the optimal dimension of judicial court can be reached by putting small courts together according to parameters derived from data analysis and proposed by experts in public sector management. Moreover, higher efficiency can also be reached exploiting economies of specialisation and adopting better organisational schemes aiming at the increase of judge productivity¹. The World Bank annually draws up the report *Doing Business* ranking countries also according to efficiency of judicial system measured as the length of civil judicial procedures. The 2009 report ranks Italy 156th out of 181 countries right below Angola, Gabon, Guinea and Sao Tome and above Gibuti, Liberia, Sri Lanka and Trinidad, whereas the last European country (Spain) ranks 54th.

The 2008 CEPEJ (European Commission for the Efficiency of Justice) report confirms the results just mentioned. On the one hand, the report shows that the human resources allocated to justice in Italy are close to those allocated by more efficient European countries (11 judges each 100,000 citizens in Italy, 11.9 in

¹ This solution cannot be applied to small judicial court where the same judge often deals with both civil and criminal law.

France and 10.1 in Spain). On the other hand, Italy appears at the end of the ranking for the length of civil judicial procedures (507 days in Italy, 262 in France and 261 in Spain), whereas Italy ranks first when we look at the numbers of *lis pendens* (more than 3.5 millions).

In the last years the public spending in justice has been decreasing both in absolute and relative values. The weight of public spending for justice on the Italian balance changed from 1.22% in 2006 to 1% in 2009, corresponding to 7.56 billions. The Italian Commission for the Public Spending Review (2008), in its final report, investigated the efficiency of the Italian justice system. The main sources of inefficiency were found to be the presence of economies of scale, the delay in adopting new information and communication technologies to conduct the proceedings faster, how legal fees are determined especially for civil proceedings. Thus, the investigation of efficiency in the provision of justice seems to attract the attention of both academic scholars and institutional bodies. In this context, it is indispensable to analyse the allocation of public resources in the judiciary and its performance.

In this context, the aim of our work is to evaluate the technical efficiency of Italian Districts of Appeal Courts of Justice (*Distretti di Corte di Appello*), also known as Judicial Districts (hereafter, JD), regarding civil proceedings and to investigate its determinants. For this purpose, starting from the approach put forward by Marselli and Vannini (2004), we analyse the relative technical efficiency of JD referring to civil cases only using non-parametric techniques and, subsequently, we estimate the determinants of relative technical efficiency.

Our analysis differs from that of Marselli and Vannini (2004) in several aspects. First, the efficiency analysis focuses only on the estimated numbers of civil cases for each JD as proposed by Carmignani and Giacomelli (2009). Thus, our efficiency analysis at judicial district level is more robust than in Marselli and Vannini (2004) given the higher degree of homogeneity of our data that makes clear which factors affect the performance of civil judicial sector. Second, we estimate the efficiency of each JD using DEA technique with a rigourous control for the not too large dimension of the sample.

The selection of the most appropriate inputs and outputs has been limited by data availability and it has been built both on previous literature and on the use of a stepwise selection algorithm introduced by Wagner and Shimshak (2007).

To check for robustness of our efficiency estimate, two procedures are considered. First, we use the smoothed homogeneous bootstrap procedure (Simar and Wilson, 1998) that investigates bias, variance, and confidence intervals of the attained efficiency scores, to get more reliable efficiency rankings, and, second, we employ the unconditional hyperbolic α -quantile estimator proposed by Wheelock and Wilson (2008) to control for the small sample dimension.

The second part of the empirical analysis will focus on the choice of the environmental variables (non-discretionary inputs) that seem to affect the efficiency of Decision-Making Units (DMU) the most. There are several approaches to the choice of environmental variables in the literature.

A first approach suggests to include environmental variables as inputs when estimating the efficiency frontier. Alternatively, it is possible to perform the second-stage analysis running a regression with the efficiency scores as dependent variables and the environmental variables as the independent ones (Cordero-Ferrera et al, 2008).

In our empirical analysis, we have opted for the second approach. When running the two-stage approach, researchers usually adopt censored regression techniques (Tobit) or, in a few cases, OLS estimates to take into account the censored nature of dependent variable. The most recent literature shows that the estimates are biased because of serial correlation of efficiency scores and suggests to apply semi-parametric two-stage technique to estimate efficiency scores using non-discretionary inputs (Simar and Wilson, 2007). To further validate the study of efficiency determinants, we obtained robust results using different techniques in the two-stage analysis to allow comparisons between parametric and semi-parametric estimation approaches.

The paper is organised as follows: Section 2 surveys the literature on the topic and presents the methodology framework. Section 3 presents the data and DEA results. Section 4 presents the second-stage regression and finally Section 5 presents the some concluding remarks.

II. JUDICIAL DISTRICTS EFFICIENCY

1. Brief literature review

The beneficial effects of an efficient judicial system of economic growth and competition are well-established in the literature (Mauro, 1995; Levine, 1998, Messick, 1999; Feld and Voigt, 2003). At the same time, the public-good nature of the judicial system poses some problems in optimally allocating the available resources to secure the access to all citizens and to provide the judicial service efficiently. On this matter, the CEPEJ has recently undertaken an analysis of the functioning of the justice system in all European states to propose concrete solutions to improve fairness, quality and efficiency of justice in Europe.

Surprisingly, few works have empirically analysed the factors causing dysfunctions of judicial systems from all over the world mainly due to the lack or incompleteness of available data. Also the analysis of efficiency in the case of justice poses other several difficulties (Marselli and Vannini, 2004). The courts can be seen as production units producing several different services. In addition, the activity of the courts is characterised by low substitution rate between inputs such as judges, clerks and different kinds of courts (Marchesi, 2003). The public decision-maker can only vary the area under the control of a specific court of

appeal tailoring the caseload on the quality and quantity of the demand of justice originated by the territory (Antonelli and Marchesi, 1999).

In particular, the efficiency of judicial districts has been undertaken mostly applying a non-parametric technique called Development Efficiency Analysis (DEA)² that overcomes all the problematic assumptions needed when building a production function following parametric techniques. Lewin et al. (1982) studied the efficiency of judicial districts of North Caroline, whereas Kittelsen and Føresund (1992) investigated the Norwegian courts of first instance. Tulkens (1993) looked at the system of judges of peace in Belgium and Pedraja-Chaparro and Salinas-Jiménez (1996) analysed the efficiency levels of administrative courts in Spain. More recently, Marselli and Vannini (2004) presents a work on the efficiency of judicial system employing data on the Italian courts of appeal finding high levels of inefficiency mainly due to an excessive caseload; that the caseload accumulated through years cannot be resolved increasing the efficiency; that some judicial districts are affected by strong variable returns to scale. Schneider (2005) focused on the performance of German labour courts of appeal showing that employing judges with Ph.D. increases the productivity but their decisions are more often overruled by the Federal Labour Court. The author also found that courts employing judges with higher ex-ante promotion probabilities are less productive and write decision that are less often confirmed. Finally, Gorman and Ruggiero (2009) evaluated the efficiency of prosecutor office in the United States showing that prosecutor offices are more efficient in more socioeconomically disadvantaged counties.

2. Measuring technical efficiency

The DEA methodology calculates an efficiency frontier for a set of DMUs, as well as the distance to the frontier for each unit. This distance (efficiency score) between observed DMU and the most efficient DMU gives a measure of the radial reduction in inputs that could be achieved for a given measure of output.

The technique has also the advantage of being very flexible, as it does not require any functional assumptions on production technologies. As illustration³ a DEA input-oriented efficiency score θ_i is calculated for each *DMU* solving the following program, for i=1,..., n, in the case of constant returns to scale (CRS):

 $^{^{2}}$ A work that it is not based on DEA is by Rosales-López (2008). The author investigated the performance of first instance courts in Spain and determined whether achieving low reversal rates and a high level of output are incompatible goals in the judiciary system.

³ For more details refer to Coelli et al. (1998) and Fried et al. (2008).

$$\begin{array}{ll} \operatorname{Min}_{\lambda,\theta_{i}} & \theta_{i} \\ \text{subject to} & -y_{i} - Y\lambda \ge 0 \\ & \dot{e}_{i}x_{i} - X\lambda \ge 0 \\ & \lambda \ge 0 \end{array} \tag{1}$$

where x_i and y_i are respectively the input and output of *i-th DMU*; X is the matrix of input and Y is the matrix of output of the sample; λ is a $n \times 1$ vector of constants. The model [1] can be modified to account for VRS (variable returns to scale) by adding the convexity constraint, $I'\lambda = 1$, which allows to distinguish between Technical Efficiency (TE) and Scale Efficiency (SE).⁴

As shown in the previous section, several works focusing on the efficiency of courts made use of the Data Envelopment Analysis (DEA), that is a wellestablished and useful technique for measuring efficiency in public sector. But some concerns need to be addressed before DEA can be accepted as a routine tool in applied analysis. Since DEA is an estimation procedure that relies on extreme points, it could be extremely sensitive to data selection, aggregation, model specification, and data errors. Notwithstanding, most researchers have largely ignored the statistical properties of DEA estimators obtaining biased DEA estimates and misleading results.

Hence, our study addresses how the Simar and Wilson (1998, 2000) smoothed homogeneous bootstrap procedure can be used to investigate bias, variance, and confidence intervals for the attained efficiency scores to get more reliable efficiency rankings.

Moreover, other two well-known problems affecting DEA use refer to the sensitivity to outliers and the curse-of-dimensionality. To control for these two effects, we use non-parametric, unconditional hyperbolic α -quantile estimator, proposed by Wheelock and Wilson (2008), that is robust with respect to outliers and is asymptotically normal.

III. EFFICIENCY ESTIMATE

1. Data

The analysis of efficiency refers to the activity of both first and second instance courts of justice falling into the regional areas over which Judicial Districts have

⁴The acronyms CRS (constant returns to scale) and VRS (variable returns to scale) are often used in reference to CCR and BCC models that come from the initial of the authors Charnes *et al.* (1978) and Banker *et al.* (1989). The choice between CRS and VRS is fundamental and depends crucially on various factors related to the context and scope of the analysis. In particular, we notice that CRS is usually more appropriate when data are characterised by long time intervals and small DMU samples (Smith, 1997).

the competence. In Italy, there are 29^5 JD, each based in the main town of the region, although the most populated regions have two.

Our study investigates the efficiency measurement of the activity of 27 judicial districts devoted to civil cases only in 2006. The data have been obtained from several sources. The number of judges and administrative staff have been estimated according to Carmignani and Giacomelli (2009). Civil litigation⁶ data come from the civil justice statistics recorded by the courts of justice and published yearly by the Italian Statistical Institute (ISTAT). As common to this stream of literature, the variable selection has been strongly influenced by the availability of data. However, as it will be discussed in the following section, the chosen variables directly refer to the activity of the courts and are supported by the existing literature on variables selection methods.

A common problem in the above-mentioned empirical studies is given by the limited sample dimension. This a severe problem in DEA estimate in particular in VRS assumption. In fact the consistence of the efficiency estimator under VRS converge a slowly rate. The rate of convergence depend from the number of observations, that is, the number of inputs and outputs⁷.

In the next section, we will control for the sample dimension problem using the stepwise selection algorithm introduced by Wagner and Shimshak $(2007)^8$ to choose the most simple specification.

2 Inputs and outputs

The selection of inputs and outputs is usually a major issue in the literature on efficiency analysis. As already mentioned, the assessment of courts efficiency poses several problems in gathering data and, as a consequence, in choosing the most appropriate inputs and outputs. For example, Kittelsen and Forsund (1992) use the posts of judges and the office staff as inputs and the number of legal proceedings referring to seven kinds of offence as outputs. Differently, Tulkens (1993) adopts the consistency of the staff working in each court as input and the number of resolved civil proceedings, the number of judgements on arbitrates in the field of family law and the number of resolved proceedings on minor offences as outputs. Lewin et al., (1982) employ both controllable inputs (days of court held and number of misdemeanours in the caseload and size of the white

⁵ The Italian courts of appeal are 29. However, we did not find data regarding two courts of appeal, namely Campobasso and L'Aquila.

⁶ We did not include the civil proceedings in front of honorary judges of peace (*giudice di pace*) because, in this case, we have not been able to distinguish the number of civil cases from the number of criminal cases solved by judges of peace.

⁷ Kneip et al. (1998) called that "curse of dimensionality"

⁸ A different approach to "mitigate" this problem of DEA estimator is implemented by Daraio and Simar (2007)

population), whereas the outputs are the number of resolved cases and the number of cases pending since less than 90 days. The analysis of Pedraja-Chaparro and Salinas-Jiménez (1996) considers the workforce as input and the resolved cases, distinguishing between cases resolved through the full legal process and other resolved cases, as outputs to assess Spanish courts efficiency. The only study focusing on the efficiency of Italian courts (Marselli and Vannini, 2004) adopts the number of judges and the number of pending cases as controllable inputs and the number of cases started at the beginning of the period of observation as exogenous input, whereas the only output is given by the number of resolved legal proceedings distinguishing between civil and criminal cases.

In our study, we use a general specification of the production function of JD, considering only civil cases, with two outputs and four inputs to study their efficiency levels.

The specification of production function adopted here uses data on judges (X_1) , administrative staff (X_2) , pending cases (X_3) , intervening cases (X_4) as inputs and on civil cases (Y) as outputs in 2006⁹. Regarding the outputs, on the basis of previous studies, we employ two different outputs: the resolved cases through full legal process (Y1) and other resolved cases (Y2). The rationale for this distinction is that the production of cases resolved through the full legal process involves higher consumption of resources. Table 1 shows the descriptive statistics of employed variables.

Variable	Mean	Standard deviation	
Judges	X_1	91.44	90.88
Administrative staff	X2	502.15	414.04
Pending civil cases	X3	118,409.07	109,557.31
Intervening case	X_4	91,573.22	83,817.2
Civil cases resolved through full legal process	Y1	46,178.93	45,036.66
Other civil resolved cases	Y ₂	42,380.80	41,849.69

Table 1 – Descriptive statistics

Given that the sample of observations is small, it turns out to be necessary to estimate the specification of the production function with the lowest number of inputs and outputs. In the literature, there are several techniques showing how to perform the selection of variables to be estimated. Norman and Stoker (1991) and Sigala et al. (2004) present selection models obtained by subsequently adding

⁹ It has to be noticed that Merselli and Vannini (2004) do not employ administrative staff because of high correlation with judges. The use of judges and administrative staff as a input prevents us from taking into account inputs related to capital, consumables and other services, although this assumption is common in the relevant literature that considers the Courts as labour-intensive units.

variables correlated with efficiency scores coming from a simple model. Other selection models suggest to exclude variables according to correlation or regression techniques because highly correlated variables are redundant and should not be included in the analysis (Lewin et al., 1982; Jenkins and Anderson, 2003).

There are also other selection models based on different grounds. In particular, such models consider the effects of the efficiency frontier on the estimation process caused by the exclusion or the inclusion of variables (Wagner and Shimshak, 2007).

We base the analysis on the latter selection model to a CRS estimation. The simplest production function specification not affecting too much negatively the performance of DMUs entails the exclusion of administrative staff ¹⁰. As shown in Appendix A.1, alternative specifications have a strong negative impact on the DMUs efficiency scores.

Hence, we will make use of the following production function specification: Judges (X_1) and intervening cases (X_4) as a input and Civil cases resolved through full legal process (Y_1), and Other civil resolved cases (Y_2) as a output . Table 2 shows the results of the efficiency analysis of JD performance¹¹. The results are in line with previous studies. From the 27 DMUs analysed, nine (33%) are relatively efficient under CRS hypothesis, whereas the number of efficient DMUs increases to nineteen (70%) if VRS are considered instead. Also the mean efficiency of the 27 DMUs is 97% under VRS and 94% under CRS. The mean efficiency of inefficient units is 91% under CRS and 96% under VRS.

Judicial district	Technical efficiency, constant returns-to- scale CRS model	Technical efficiency, variable returns- to-scale VRS model	
# Efficient DMUs	9	19	
# Inefficient DMUs	18	9	
Mean (all sample)	0.940	0.974	
Mean inefficient unit	0.909	0.960	
SD	0.063	0.053	

In order to test the hypotheses of variable returns to scale, we have run three regressions to analyse the relationship between the efficiency scores (CRS) and the size of the Judicial district using the number of judges, the total number of staff and the population served as proxies for dimension. Since efficiency scores are truncated from below at one, we have used the truncated regression. Neither variable turns out to be significant. This supports the use of the CRS assumption in the following analysis. Table 3 summarises the results.

¹⁰ The choice of dropping the administrative staff causes an average change of efficiency of 0.0163 as shown in Appendix A.1.

¹¹ See Appendix A.2. for more details.

X7 . 11	(1)	(2)	(3)
Variables	Score CRS	Score CRS	Score CRS
Tudaa	-0.000		
Judge	(0.33)		
a		-0.000	
Staff		(0.10)	
Dopulation			-0.000
Population			(0.34)
	0.944***	0.941***	0.944***
Constant	(55.52)	(49.79)	(50.57)
Observations	27	27	27

Table 3. Truncate regression of the efficiency scores (CRS) on the size of the Judicial district

Absolute value of z statistics in parentheses;

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

3. Robustness check

In order to check for the robustness of our findings, we performed two alternative tests that we thought to be relevant.

First, we implement the homogeneous bootstrap procedure to correct the bias in DEA estimators and obtain their confidence intervals. The confidence intervals and the bias-corrected efficiency scores have been estimated using the homogeneous bootstrap procedure with 2,000 bootstrap draws as described by Simar and Wilson (1998). Data (available in the Appendix A.3) show that biases may have strong effects on efficiency scores.

Second, we use non-parametric, unconditional hyperbolic α -quantile estimator proposed by Wheelock and Wilson (2008) to control for outlier and for sample dimension. This estimator is robust with respect to outliers and is asymptotically normal.

IV. THE DETERMINANT OF TECHNICAL EFFICIENCY OF JUDICIAL DISTRICTS

In the previous section, the efficiency scores of JD shown a quite high degree of variability. Here, we will investigate which environmental factors may influence the efficiency levels under CRS.

A two-step, biased-corrected efficiency method proposed by Simar and Wilson (2007) is used to analyse the relation between scores and a set of environmental variables in the following general specification:

$$\theta_i = f(z_i) + \varepsilon_i$$
 [2]

Where θ represents the CRS efficient score that resulted from previous stage, z_i is a set of possible non-discretionary inputs and ε_i is a vector of error terms. The choice of CRS efficient scores is based on several issues: first, CRS usually shows more variation than VRS scores. Second, CRS scores identify overall inefficiency, and, finally, the regression test, run in the previous section, supports the use of the CRS assumption.

In the second-stage analysis we will include as non-discretionary inputs, the *per capita* caseload (caseload for each judge working on civil cases only); an index of specialisation, obtained as a ratio between the number of civil cases and the total amount of cases; a litigation ratio (number of intervening cases each 100.000 inhabitants). Table 4 shows the descriptive statistics of non-discretionary inputs included in the analysis, whereas Table 5 reports the results of second-stage estimation.

Variable	Obs	Mean	Std. Dev.	Min	Max
CRS Efficiency Scores	27	89.34	5.86	78.30	97.00
Caseload per capita	27	2466.19	950.75	1216.00	5414.00
Index of Specialization	27	59.19	9.79	42.00	85.00
Litigation Ratio	27	1061.09	313.90	593.00	2039.00

Table 4 – Descriptive statistics

Source: Carmignani and Giacomelli (2009).

	(1)	(2)
	Eff. Bias-Corrected	Eff. Bias-Corrected
Caseload per capita	-0.001	-0.001
Caseload per capita	(0.33)	(0.36)
Index of Specialization	0.144	0.144
Index of Specialization	(0.79)	(0.86)
Litigation Ratio	-0.000	-0.000
	(0.11)	(0.12)
Constant	82.801***	82.801***
Constant	(9.70)	(10.51)
Observations	27	27
R-squared	0.03	

Table 5 – Estimation result

Absolute value of t statistics in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%

Surprisingly, none of environmental variables suggested by the literature turned out to significantly affect the CRS efficiency scores. The high significance of the constant term shows that many factors have been left unexplored yet. Hence, a more detailed analysis of non-discretionary inputs has already started to get a more informative results form the second-stage of our empirical investigation.

V. CONCLUSIONS

Our empirical analysis has focused first on the computation of efficiency scores of 27 Italian judicial districts on civil cases in 2006. For this purpose, we used the DEA model that allows for the incorporation of multiple inputs and outputs in determining relative efficiencies. Benchmarks are provided for improving the activity of poorly performing judicial districts.

During the analysis, it became obvious that, while DEA has been widely adopted in the literature on judicial efficiency and productivity studies, it has merits as well as limitations. To overcome the latter, we used the two-step, biased-corrected efficiency method, proposed by Simar and Wilson (2007), to investigate the relation between scores and a set of environmental variables.

The proposed technique is superior in many ways to the techniques currently found in the literature on judicial system efficiency. Thus, the contribution of this paper to the literature with respect to technique is threefold: to improve the existing methods using DEA, by comparing and contrasting relative approaches and variations; by combining DEA technique with a recently developed Simar– Wilson method, and using this method to bootstrap the DEA scores with a truncated regression, to better (from an econometric viewpoint) explain DEA efficiency levels; and to present the broader relevance of the analysis.

Specifically, this new procedure has offered some improvement in both efficiency of estimation and inference in the second stage. By adopting the functional form (or truncated functional form) in the second stage, it has enabled consistent inference with models to explain efficiency scores while simultaneously producing standard errors and confidence intervals for these efficiency scores.

However, at the present stage of the analysis, none of the environmental variables included have been able to significantly explain the efficiency scores. Hence, more research is needed to improve our preliminary results.

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Appendix

A.1 – Stepwise input selection

Unit name Score Score Score Score Ancona 1.000 1.000 1.000 0.00 Bari 1.000 1.000 1.000 1.000 Bologna 0.913 0.913 0.913 0.913 Bologna 0.913 0.913 0.913 0.913 Bologna 0.913 0.913 0.913 0.913 Bologna 0.913 0.817 0.827 0.01 Brescia 1.000 1.000 1.000 1.000 Caltanisetta 0.869 0.867 0.01 0.01 Catanzaro 0.875 0.875 0.841 0.01 Genova 1.000 1.000 1.000 0.01 Lecce 1.000 0.992 0.991 0.3 Milano 0.926 0.926 0.925 0.01 Napoli 1.000 1.000 1.000 0.00 Perugia 0.876 0.876 0.37 0.37		(1)	(2)	(3)	(4)
Variable dropped Administrative staff Pending civil cases Starting ca Variable dropped Score	Input	4	3	2	1
Unit name Score Score Score Score Ancona 1.000 1.000 1.000 0.00 Bari 1.000 1.000 1.000 1.000 Bologna 0.913 0.913 0.913 0.913 Bologna 1.000 1.000 1.000 1.000 1.000 Caliaris 0.832 0.827 0.827 0.37 Catania 0.830 0.817 0.817 0.31 Genova 1.000 1.000 1.000 1.000 1.000 Lecce 1.000 0.992 0.991 0.31 Massina 0.897 0.897 0.897 0.32 Palermo 1.000 0.985 0.985	Output	2	2	2	2
Ancona 1.000 1.000 1.000 1.000 Bari 1.000 1.000 1.000 1.000 Bologna 0.913 0.913 0.913 0.913 Bologna 0.913 0.913 0.913 0.913 Bologna 1.000 1.000 0.991 0.0 Brescia 1.000 1.000 1.000 1.000 Caliari 0.832 0.827 0.827 0.3 Catania 0.830 0.817 0.817 0.3 Catanzaro 0.875 0.875 0.841 0.0 Frenze 1.000 1.000 1.000 1.000 Genova 1.000 0.992 0.991 0.3 Messina 0.897 0.897 0.897 0.6 Mapoli 1.000 0.985 0.985 0.3 Palermo 1.000 1.000 1.000 0.0 Reggio Calabria 1.000 0.986 0.940 0.0 <t< td=""><td>Variable dropped</td><td>-</td><td>Administrative staff</td><td>Pending civil cases</td><td>Starting case</td></t<>	Variable dropped	-	Administrative staff	Pending civil cases	Starting case
Bari 1.000 1.000 1.000 1.000 Bologna 0.913 0.913 0.913 0.913 Bolzano 1.000 1.000 0.991 0.9 Brescia 1.000 1.000 1.000 1.000 Cagliari 0.832 0.827 0.827 0.0.2 Caltanisetta 0.830 0.817 0.817 0.0.2 Catania 0.830 0.817 0.817 0.0.2 Catanaro 0.875 0.875 0.841 0.0 Firenze 1.000 1.000 1.000 1.000 Genova 1.000 0.992 0.991 0.3 Messina 0.897 0.897 0.897 0.897 Milano 0.926 0.926 0.925 0.3 Palermo 1.000 1.000 1.000 0.0 Reggio Calabria 1.000 0.986 0.940 0.0 Reggio Calabria 1.000 0.918 0.918 0.0	Unit name	Score	Score	Score	Score
Bologna 0.913 0.913 0.913 0.913 0.913 Bolzano 1.000 1.000 0.991 0.1 Brescia 1.000 1.000 1.000 1.000 Cagliari 0.832 0.827 0.827 0.2 Caltanisetta 0.869 0.869 0.867 0.2 Catania 0.830 0.817 0.817 0.3 Catanzaro 0.875 0.875 0.841 0.7 Genova 1.000 1.000 1.000 1.000 Lecce 1.000 0.992 0.991 0.3 Milano 0.926 0.926 0.925 0.7 Napoli 1.000 0.985 0.985 0.3 Palermo 1.000 0.986 0.940 0.7 Sasari 0.919 0.918 0.940 0.4 Sasari 0.919 0.918 0.918 0.4 Trento 1.000 1.000 1.000 0.7 0.7	Ancona	1.000	1.000	1.000	0.957
Bolzano 1.000 1.000 0.991 0.1 Bolzano 1.000 1.000 1.000 1.000 1.000 Brescia 1.000 1.000 1.000 1.000 1.1 Cagliari 0.832 0.827 0.827 0.3 Caltanissetta 0.869 0.869 0.867 0.3 Catania 0.830 0.817 0.817 0.3 Catanzaro 0.875 0.875 0.841 0.3 Genova 1.000 1.000 1.000 1.000 Lecce 1.000 0.992 0.991 0.3 Messina 0.897 0.897 0.897 0.697 Milano 0.926 0.926 0.925 0.3 Palermo 1.000 1.000 1.000 0.0 Perugia 0.876 0.876 0.376 0.37 Potenza 0.834 0.834 0.4 0.4 Salerno 1.000 1.000 1.000 <	Bari	1.000	1.000	1.000	1.000
Brescia 1.000 1.000 1.000 1.000 Cagliari 0.832 0.827 0.827 0.2 Caltanissetta 0.869 0.869 0.867 0.2 Catania 0.830 0.817 0.817 0.2 Catania 0.830 0.817 0.817 0.2 Catanzaro 0.875 0.875 0.841 0.2 Genova 1.000 1.000 1.000 1.000 Lecce 1.000 0.992 0.991 0.2 Messina 0.897 0.897 0.897 0.6 Napoli 1.000 0.985 0.985 0.3 Palermo 1.000 1.000 1.000 0.0 Perugia 0.876 0.876 0.37 0.3 Reggio Calabria 1.000 1.000 1.000 0.0 Sasari 0.919 0.918 0.918 0.4 Grand 1.000 1.000 1.000 1.000 <t< td=""><td>Bologna</td><td>0.913</td><td>0.913</td><td>0.913</td><td>0.913</td></t<>	Bologna	0.913	0.913	0.913	0.913
Cagliari 0.832 0.827 0.827 0.927 Caltanissetta 0.869 0.869 0.867 0.1 Catania 0.830 0.817 0.817 0.1 Catania 0.830 0.817 0.817 0.1 Catanzaro 0.875 0.875 0.841 0.1 Genova 1.000 1.000 1.000 1.000 0.1 Genova 1.000 0.992 0.991 0.3 Messina 0.897 0.897 0.897 0.6 Milano 0.926 0.926 0.925 0.1 Napoli 1.000 1.000 1.000 0.0 Palermo 1.000 0.985 0.985 0.3 Potenza 0.834 0.834 0.6 0.0 Reggio Calabria 1.000 1.000 1.000 0.0 0.0 Salerno 1.000 1.000 1.000 0.0 0.0 0.0 Sasari 0.919 0	Bolzano	1.000	1.000	0.991	0.657
Caltanissetta 0.869 0.869 0.867 0 Catania 0.830 0.817 0.817 0 Catania 0.830 0.817 0.817 0 Catanzaro 0.875 0.875 0.841 0 Firenze 1.000 1.000 1.000 1.000 Genova 1.000 0.992 0.991 0 Messina 0.897 0.897 0.897 0 Milano 0.926 0.926 0.925 0 Napoli 1.000 1.000 1.000 0 Palermo 1.000 0.985 0.985 0 Potenza 0.834 0.834 0 0 Reggio Calabria 1.000 1.000 1.000 0 Sasari 0.919 0.918 0.948 0 Taranto 1.000 1.000 0 0 Treito 1.000 1.000 0 0 0 </td <td>Brescia</td> <td>1.000</td> <td>1.000</td> <td>1.000</td> <td>1.000</td>	Brescia	1.000	1.000	1.000	1.000
Catania 0.830 0.817 0.817 0.1 Catanzaro 0.875 0.875 0.817 0.1 Firenze 1.000 1.000 1.000 1.000 Genova 1.000 1.000 1.000 0.000 Lecce 1.000 0.992 0.991 0.1 Messina 0.897 0.897 0.897 0.7 Milano 0.926 0.926 0.925 0.1 Napoli 1.000 0.985 0.985 0.3 Palermo 1.000 1.000 1.000 0.0 Potenza 0.834 0.834 0.834 0.3 Reggio Calabria 1.000 1.000 1.000 0.0 Salerno 1.000 1.000 1.000 1.000 1.000 Salerno 1.000 1.000 1.000 0.918 0.0 Taranto 1.000 1.000 1.000 0.925 0.3 Trento 1.000 1.000 <	Cagliari	0.832	0.827	0.827	0.548
Catanzaro 0.875 0.875 0.841 0. Firenze 1.000 1.000 1.000 1.000 1.000 Genova 1.000 1.000 1.000 0.00 0. Lecce 1.000 0.992 0.991 0. 0. Messina 0.897 0.897 0.897 0. Milano 0.926 0.926 0.925 0. Napoli 1.000 0.985 0.985 0. Palermo 1.000 1.000 1.000 0. Perugia 0.876 0.876 0.876 0. Potenza 0.834 0.834 0.834 0. 0. Reggio Calabria 1.000 1.000 1.000 0. 0. 0. Salerno 1.000 1.000 1.000 1.000 0. 0. Sasari 0.919 0.918 0.918 0. 0. 0. Trento 1.000 1.000 0.00	Caltanissetta	0.869	0.869	0.867	0.505
Firenze 1.000 1.000 1.000 1.000 Genova 1.000 1.000 1.000 0.0 Lecce 1.000 0.992 0.991 0.3 Messina 0.897 0.897 0.897 0.7 Milano 0.926 0.926 0.925 0.7 Napoli 1.000 0.985 0.985 0.3 Palermo 1.000 1.000 1.000 0.7 Perugia 0.876 0.876 0.876 0.5 Potenza 0.834 0.834 0.834 0.6 Reggio Calabria 1.000 1.000 1.000 0.0 Roma 1.000 1.000 1.000 0.4 Salerno 1.000 1.000 1.000 1.0 Salerno 1.000 1.000 0.952 0.4 Tranto 1.000 1.000 0.952 0.4 Trento 1.000 1.000 0.932 0.4 Trieste	Catania	0.830	0.817	0.817	0.576
Genova 1.000 1.000 1.000 0.000 Lecce 1.000 0.992 0.991 0.3 Messina 0.897 0.897 0.897 0.7 Milano 0.926 0.926 0.925 0.7 Napoli 1.000 0.985 0.985 0.7 Palermo 1.000 1.000 1.000 0.7 Perugia 0.876 0.876 0.876 0.7 Potenza 0.834 0.834 0.834 0.7 Reggio Calabria 1.000 1.000 1.000 0.7 Sasari 0.919 0.918 0.918 0.4 Taranto 1.000 1.000 0.952 0.7 Treto 1.000 1.000 0.932 0.7 Trieste 0.927 0.927 0.944 0.7 Mean eff 0.950 0.948 0.940 0.7	Catanzaro	0.875	0.875	0.841	0.770
Lecce 1.000 0.992 0.991 0.3 Messina 0.897 0.897 0.897 0.7 Milano 0.926 0.926 0.925 0.7 Napoli 1.000 0.985 0.985 0.8 Palermo 1.000 0.985 0.985 0.7 Perugia 0.876 0.876 0.8 0.7 Potenza 0.834 0.834 0.834 0.7 Reggio Calabria 1.000 1.000 1.000 0.7 Reggio Calabria 1.000 0.986 0.940 0.7 Salerno 1.000 1.000 1.000 1.0 1.0 Sassari 0.919 0.918 0.918 0.7 Taranto 1.000 1.000 1.000 0.7 Trieste 0.927 0.927 0.932 0.7 Mean eff 0.950 0.948 0.940 0.7	Firenze	1.000	1.000	1.000	1.000
Messina 0.897 0.897 0.897 0.7 Milano 0.926 0.926 0.925 0.7 Napoli 1.000 0.985 0.985 0.9 Palermo 1.000 1.000 1.000 0.7 Perugia 0.876 0.876 0.876 0.7 Potenza 0.834 0.834 0.834 0.7 Reggio Calabria 1.000 1.000 1.000 0.7 Rena 0.834 0.834 0.834 0.7 Reggio Calabria 1.000 1.000 0.7 0.7 Salerno 1.000 0.986 0.940 0.7 Sassari 0.919 0.918 0.918 0.4 Taranto 1.000 1.000 1.000 0.7 Trento 1.000 1.000 0.932 0.7 Trieste 0.927 0.927 0.904 0.7 Mean eff 0.950 0.948 0.940 0.7	Genova	1.000	1.000	1.000	0.733
Milano 0.926 0.926 0.925 0.7 Napoli 1.000 0.985 0.985 0.9 Palermo 1.000 1.000 1.000 0.7 Perugia 0.876 0.876 0.876 0.7 Potenza 0.834 0.834 0.834 0.7 Reggio Calabria 1.000 1.000 1.000 0.7 Roma 1.000 0.986 0.940 0.7 Salerno 1.000 1.000 1.000 1.000 Sasari 0.919 0.918 0.918 0.7 Taranto 1.000 1.000 0.952 0.7 Trento 1.000 1.000 0.932 0.7 Trieste 0.927 0.927 0.904 0.7 Mean eff 0.950 0.948 0.940 0.7	Lecce	1.000	0.992	0.991	0.813
Napoli 1.000 0.985 0.985 0.1 Palermo 1.000 1.000 1.000 0.7 Perugia 0.876 0.876 0.876 0.1 Potenza 0.834 0.834 0.834 0.834 0.7 Reggio Calabria 1.000 1.000 1.000 0.0 Roma 1.000 0.986 0.940 0.0 Salerno 1.000 1.000 1.000 1.000 Sasari 0.919 0.918 0.918 0.0 Taranto 1.000 1.000 0.952 0.3 Trento 1.000 1.000 0.932 0.3 Treat 0.927 0.927 0.904 0.3 Mean eff 0.950 0.948 0.940 0.3	Messina	0.897	0.897	0.897	0.729
Palermo 1.000 1.000 1.000 0.000 Perugia 0.876 0.876 0.876 0.876 0.7 Potenza 0.834 0.834 0.834 0.834 0.7 Reggio Calabria 1.000 1.000 1.000 0.0 Roma 1.000 0.986 0.940 0.7 Salerno 1.000 1.000 1.000 1.000 Salerno 1.000 1.000 1.000 1.000 Sassari 0.919 0.918 0.918 0.4 Taranto 1.000 1.000 0.952 0.7 Trento 1.000 1.000 0.932 0.7 Trieste 0.927 0.927 0.904 0.7 Mean eff 0.950 0.948 0.940 0.7	Milano	0.926	0.926	0.925	0.703
Perugia 0.876 0.876 0.876 0.17 Potenza 0.834 0.834 0.834 0.834 0.634 0.6376 0.67 0.676 0.67 0.676 0.67 0.676 0.67 0.678 0.676 0.67 0.678 0.678 0.679 0.678 0.678 0.678 0.678 0.678 0.678 0.678 0.678 0.678 0.678 0.678 0.678 0.6797 0.6797 0.6797 0.6797 0.677 0.6777 0.6957 0.6777 0.6797 0.6777 0.6747 0.6747 0.6747 0.6747 0.6747 0.6747 0.6747 0.6747 0.6747 <td>Napoli</td> <td>1.000</td> <td>0.985</td> <td>0.985</td> <td>0.829</td>	Napoli	1.000	0.985	0.985	0.829
Potenza 0.834 0.834 0.834 0.834 0.7 Reggio Calabria 1.000 1.000 1.000 0.0 Roma 1.000 0.986 0.940 0.0 Salerno 1.000 1.000 1.000 1.000 Salerno 1.000 1.000 1.000 1.000 Sasari 0.919 0.918 0.918 0.0 Taranto 1.000 1.000 1.000 0.0 Torino 1.000 1.000 0.952 0.0 Trento 1.000 1.000 0.932 0.0 Trieste 0.927 0.927 0.904 0.0 Venezia 0.957 0.957 0.957 0.0	Palermo	1.000	1.000	1.000	0.704
Reggio Calabria 1.000 1.000 1.000 0.0 Roma 1.000 0.986 0.940 0.0 Salerno 1.000 1.000 1.000 1.000 Salerno 1.000 1.000 1.000 1.000 Sassari 0.919 0.918 0.918 0.0 Taranto 1.000 1.000 1.000 0.0 Torino 1.000 1.000 0.952 0.0 Trento 1.000 1.000 0.932 0.0 Trieste 0.927 0.927 0.904 0.0 Venezia 0.957 0.957 0.957 0.0	Perugia	0.876	0.876	0.876	0.869
Roma 1.000 0.986 0.940 0.0 Salerno 1.000 1.000 1.000 1.000 1.000 Sassari 0.919 0.918 0.918 0.918 0.0 Taranto 1.000 1.000 1.000 0.0 0.0 Torino 1.000 1.000 0.952 0.0 0.0 Trento 1.000 1.000 0.932 0.0 0.0 Trieste 0.927 0.927 0.904 0.0 Venezia 0.957 0.957 0.957 0.0 Mean eff 0.950 0.948 0.940 0.0	Potenza	0.834	0.834	0.834	0.759
Salerno 1.000 1.000 1.000 1.000 1.000 Sassari 0.919 0.918 0.918 0.918 0.918 Taranto 1.000 1.000 1.000 0.01 Torino 1.000 1.000 0.952 0.1 Trento 1.000 1.000 0.932 0.1 Trieste 0.927 0.927 0.904 0.1 Venezia 0.957 0.957 0.957 0.1 Mean eff 0.950 0.948 0.940 0.1	Reggio Calabria	1.000	1.000	1.000	0.698
Sassari 0.919 0.918 0.918 0.918 0.01 Taranto 1.000 1.000 1.000 0.952 0.9 Torino 1.000 1.000 0.952 0.9 0.9 Trento 1.000 1.000 0.932 0.9 0.9 Trieste 0.927 0.927 0.904 0.9 Venezia 0.957 0.957 0.957 0.9 Mean eff 0.950 0.948 0.940 0.9	Roma	1.000	0.986	0.940	0.644
Taranto 1.000 1.000 1.000 0.0 Torino 1.000 1.000 0.952 0.1 Trento 1.000 1.000 0.932 0.1 Trieste 0.927 0.927 0.904 0.1 Venezia 0.957 0.957 0.957 0.1 Mean eff 0.950 0.948 0.940 0.1	Salerno	1.000	1.000	1.000	1.000
Torino 1.000 1.000 0.952 0.1 Trento 1.000 1.000 0.932 0.1 Trieste 0.927 0.927 0.904 0.1 Venezia 0.957 0.957 0.957 0.7 Mean eff 0.950 0.948 0.940 0.1	Sassari	0.919	0.918	0.918	0.640
Trento 1.000 1.000 0.932 0.7 Trieste 0.927 0.927 0.904 0.7 Venezia 0.957 0.957 0.957 0.7 Mean eff 0.950 0.948 0.940 0.7	Taranto	1.000	1.000	1.000	0.995
Trieste 0.927 0.927 0.904 0.7 Venezia 0.957 0.957 0.957 0.7 Mean eff 0.950 0.948 0.940 0.7	Torino	1.000	1.000	0.952	0.870
Venezia 0.957 0.957 0.957 0. Mean eff 0.950 0.948 0.940 0.	Trento	1.000	1.000	0.932	0.704
Mean eff 0.950 0.948 0.940 0.7	Trieste	0.927	0.927	0.904	0.761
	Venezia	0.957	0.957	0.957	0.799
	Mean eff	0.950	0.948	0.940	0.784
Median 1.000 0.986 0.946 0.4	Median	1.000	0.986	0.946	0.760
Standard deviation 0.208 0.208 0.210 0.11	Standard deviation	0.208	0.208	0.210	0.271
Average change in efficiency 0.002 0.009 0.	Average change in efficiency		0.002	0.009	0.155
# Efficient DMUs 15.000 12.000 9.000 4.	# Efficient DMUs	15.000	12.000	9.000	4.000

 # Efficient Divids
 15.000
 12.000
 9.000
 4.000

 Note: column 1, 2, 3, and 4 show respectively the start and step 1, 2 and 3 for stepwise algoritm described in Wagner and Shimshak (2007).
 Start and step 1, 2 and 3 for stepwise algoritm described

A.2 CRS-DEA model and VRS-DEA model, technical efficiency scores for JD

Judicial district	Technical efficiency, constant returns-to-scale CRS model	Technical efficiency, variable returns-to-scale VRS model	RTS	Scale efficiency
Ancona	1.000	1.000	0	1.000
Bari	1.000	1.000	0	1.000
Bologna	0.913	1.000	0	1.096
Bolzano	0.991	1.000	0	1.009
Brescia	1.000	1.000	0	1.000
Cagliari	0.827	0.834	-1	1.009
Caltanissetta	0.867	1.000	0	1.154
Catania	0.817	0.818	1	1.001
Catanzaro	0.841	0.895	1	1.063
Firenze	1.000	1.000	0	1.000
Genova	1.000	1.000	0	1.000
Lecce	0.991	0.995	1	1.005
Messina	0.897	0.908	-1	1.012
Milano	0.925	1.000	0	1.081
Napoli	0.985	1.000	0	1.015
Palermo	1.000	1.000	0	1.000
Perugia	0.876	1.000	0	1.142
Potenza	0.834	0.971	-1	1.164
Reggio Calabria	1.000	1.000	0	1.000
Roma	0.940	1.000	0	1.064
Salerno	1.000	1.000	0	1.000
Sassari	0.918	0.951	-1	1.036
Taranto	1.000	1.000	0	1.000
Torino	0.952	1.000	0	1.050
Trento	0.932	1.000	0	1.073
Trieste	0.904	0.914	-1	1.011
Venezia	0.957	1.000	0	1.045
Mean	0.940	0.974	1	1.038
Mean inefficient unit	0.909	0.960		1.057
SD	0.063	0.053	9	0.051

A.3	Bias-corrected	efficiency	scores	for JD
	2100 001100000	••••••	500105	101 02

¥ I		Eff. Bias-	DIAG	Var	I D J	I D
Unit name	<u> </u>					Lower Bound
Genova	1.000	0.970				
Ancona	1.000	0.965				
Lecce	0.991	0.963	-0.029	0.000	0.930	0.989
Palermo	1.000	0.960	-0.042	0.001	0.906	0.997
Salerno	1.000	0.944	-0.059	0.001	0.885	0.998
Brescia	1.000	0.944	-0.059	0.002	0.869	0.998
Firenze	1.000	0.942	-0.062	0.002	0.880	0.997
Taranto	1.000	0.940	-0.064	0.002	0.870	0.998
Reggio di Calabria	1.000	0.938	-0.066	0.002	0.864	0.998
Bari	1.000	0.935	-0.069	0.003	0.850	0.997
Bolzano	0.991	0.928	-0.068	0.003	0.846	0.988
Napoli	0.985	0.921	-0.070	0.003	0.830	0.983
Venezia	0.957	0.920	-0.043	0.001	0.870	0.955
Torino	0.952	0.910	-0.048	0.001	0.861	0.950
Sassari	0.918	0.889	-0.036	0.000	0.856	0.916
Roma	0.940	0.881	-0.072	0.003	0.803	0.937
Trento	0.932	0.881	-0.063	0.002	0.821	0.930
Trieste	0.904	0.878	-0.034	0.000	0.847	0.902
Messina	0.897	0.873	-0.032	0.000	0.851	0.895
Milano	0.925	0.863	-0.077	0.003	0.778	0.923
Bologna	0.913	0.856	-0.072	0.003	0.789	0.910
Perugia	0.876	0.822	-0.075	0.003	0.757	0.873
Caltanissetta	0.867	0.812	-0.078	0.004	0.730	0.865
Cagliari	0.827	0.808	-0.028	0.000	0.788	0.825
Catanzaro	0.841	0.799	-0.064	0.001	0.757	0.839
Catania	0.817	0.797	-0.030	0.000	0.775	0.815
Potenza	0.834	0.783	-0.079	0.003	0.721	0.832
Mean eff	0.940	0.893			0.837	
SD	0.063	0.059			0.060	0.063

Note: figures are ranked according to bias-corrected efficiency scores.