Disentangling unobserved heterogeneity and technical efficiency: Evidences from a panel of Italian hospitals.*

Vincenzo Atella
University of Rome Tor Vergata

Federico Belotti
University of Rome Tor Vergata

Silvio Daidone
University of York

Giuseppe Ilardi
Bank of Italy

Giorgia Marini
University of Rome Tor Vergata

November 2010

Abstract

The aim of this paper is to provide an assessment of the evolution of technical efficiency in a large longitudinal database of Italian hospitals over the period 1999-2007 by means of a parametric analysis based on stochastic frontier approach. In particular, we evaluate to which extent the set of national and regional cost control policies implemented over this period and the bail-out programs signed with specific regions has affected hospital activities. From a methodological point of view, we implement a "true" random effects estimator and jointly estimate the technology and the inefficiency equations. In this way we are able *i)* to disentangle cross hospital unobserved heterogeneity from hospital inefficient behavior and *ii)* to provide more precise estimates of both technology and efficiency. All estimates are obtained using a *Bayesian* stochastic frontier technique. Results shows some changes in the technical efficiency of hospitals over time and the existence of non negligible level of heterogeneity by ownership status.

JEL Codes:

Keywords: Hospital efficiency, Stochastic frontiers, Bayesian estimation, Bailout plan.

PRELIMINARY AND INCOMPLETE DRAFT
PLEASE DO NOT QUOTE WITHOUT AUTHOR PERMISSION

*Corresponding author: Vincenzo Atella, Faculty of Economics, University of Rome Tor Vergata, Via Columbia, 2, 00133 Rome, Italy; e-mail: atella@uniroma2.it, tel. +39 06 7259 5635

1 Introduction

Over the last two decades, public health care spending in Italy experienced a constant increase, following a pattern which is common to many OECD countries (OECD, Health data - 2009). In particular, expenditure grew from 41.2 billions of euros in 1990 to almost 109.7 billions in 2009, while as a share of the economy, health care rose from 5.9% of GDP to 7.2% (RGS (1994) and RGS (2010)).

Despite the huge effort made by the government in more than doubling the financial resources invested in the sector, the global sentiment of Italian patients is that the amount and quality of the health care services received has not changed that much. It is worth noting that about 50% of these resources are allocated to hospital care, that despite the many requests from some stakeholders still remains the less accountable and transparent part of the Italian health sector, often rising serious doubts about its level of overall efficiency.

As in many other countries, concerns about efficiency levels in the health care sector have always been part of the Italian policy debate. Since 1992, several reforms have been introduced, with the main aim of improving efficiency of service provision while curbing the health care bill. In particular, the hospital sector has witnessed several changes, mostly related to the organization and delivery of services and to the reimbursement mechanism.

With respect to the former two aspects, we observe two key changes: the creation of an internal quasi-market for health care and the decentralization of health care expenditures at regional level. Purchasing and providing functions were partially split: local health authorities (LHA) became the purchasing units, while a vast array of organizations with different ownership structures competed with each other for the delivery of services.[1]

Regarding the payment system, starting from 1995, the reimbursement mechanism for all hospitals operating within the NHS switched from a financing system based on historical costs (bed-day rates for private structures and ex-post payments for public ones) to a prospective payment system (PPS), for both inpatient and outpatient procedures. Note that, regardless of the ownership, the reimbursement for inpatient care is based on diagnosis related groups (DRGs), while reimbursement for outpatient care, either diagnostic services or specialist treatments, should be based on fee for service. Clearly, the idea was to discourage the unpleasant ongoing behavior on the side of hospital managers of generating costs just to guarantee more financing in the future.

Despite this important change in the financing procedure and the fact that management of health care services was transferred from the State to the Regions (that were supposed to able to match better the local needs of the population with the provision of health care services), the hospital sector has been widely recognized as the main responsible of the public health care deficit. In fact, despite the existence of a PPS, public hospital have always been re-financed *ex-post* if revenues from PPS were lower than realized costs.

This unpleasant behavior starts to change with the launch in 2001 of a federalist reform of the State, that by imposing (among other things) more financial responsibility on the single Regions, has witnessed the implementation of a variety of local policies aimed at controlling the upsurge of expenditure. Furthermore, in 2006 the Ministry of Economics has introduced tighter financial and economic measures to contain the aggregate public budget deficit as imposed by the European Monetary Union.

As result of these national and regional policy changes,the cost control measures that have emerged at regional level have been highly heterogeneous. In fact, while some regions (mostly in the Center-North) have been able to reach a substantial balance in their health care budgets, for some of them (Lazio and Campania in particular) the debt accumulated up to 2006 has been so high to require an *ad hoc* bail-out plan. As in Italy regional public budget are largely made by public health care budgets (on average they accounts for about 75% of total budget (RGS (2010))) and because half of health care budgets is absorbed by the delivery of care at hospital level, it remains compulsory for any economic analysis in this sector to study the evolution of the public hospitals. Potentially, we expect that regions whose economic and financial outcomes since 1996 have evolved in a more performing way should also be those who have been more able to reorganize and rationalize the hospital sector, thus leading to an improvement in the efficiency levels of this sector over time.

To this end, we perform a parametric analysis based on stochastic frontier approach to measure the evolution of technical efficiency in a longitudinal database of Italian hospitals over the period 1999-2007, period for which a comprehensive set of data at hospital level is available in Italy. Our goal is to evaluate to

[1] In Italy, hospital care providers range from private for-profit firms to structures directly managed by LHAs and include public and private teaching hospitals, public and private research institutes, public trusts formally independent from the purchasers. More details regarding the ownership status are provided in section .

which extent the set of national and regional cost control policies implemented and the bail-out programs signed with specific regions has affected hospital activities. Thanks to the detailed information at hospital level, we are able to study efficiency changes by region, ownership status, degree of capitalization and level of specialization of hospitals. [2] Unfortunately for the Italian case, due to lack of hospital level financial data, we are forced to focus our analysis only to technical efficiency.

From a methodological point of view, we innovate under several aspects with respect to previous literature. In particular, for the first time in the hospital sector, we implement the Greene (2005) "true" random effects estimator on a model and jointly estimate the technology and the inefficiency equations. In this way we are able *i)* to disentangle cross hospital unobserved heterogeneity from hospital inefficient behavior and *ii)* to provide more precise estimates of both technology and efficiency. All estimates are obtained using *Bayesian* stochastic frontier technique, and we critically assess the pros of using such technique compared to the standard in literature *frequentist* approach. As it will be clearer in the following pages, we are able to justify our choice in terms of parameter identification problem, on the ground of information obtained from the signal to noise ratio between the variance of unobserved heterogeneity and the variance of error component term. Furthermore, we use the larger and most complete available dataset on Italian hospital as provided by the Italian Ministry of Health. We have an unbalanced panel of hospitals over the period 1999-2007, across all regions. This will allow to analyze efficiency differences in terms of regional location, ownership structures (an extension of previous studies), degree of specialization and, for the first time, we will investigate the role that bailout plans (piani di rientro) may have had on the efficiency level.

In what follow the paper is organized in six sections. Section two present a short review of the literature, focusing on what has already been done in Italy to measure hospital technical efficiency. Section three discusses the reasons that have induced us to opt for a bayesian approach and present the econometric model. Section four introduces to the data. Section five present the empirical results. Finally, section six concludes.

2 A brief review of the literature on hospital efficiency

In a recent published paper **?** highlights that since the early 1980s, there has been an increasing interest toward measuring the productive performance of health care services. More than half of these studies (55%) have been published since 2000. Of all these studies only 18% have adopted a parametric approach (mainly SF), while 52% of all empirical applications have focused on hospital efficiency. Furthermore, technical efficiency is by far the most studied aspect. Results in terms of efficiency vary greatly depending on type of hospital, country of origin and type of analysis performed, although what seems to emerges as general rule is that EU hospitals are more efficient than US hospitals.

Concerning Italy, apart from a study conducted by **?** on a small panel of hospitals, no further evidence have been reported by **?** on Italian hospital sector. Evidence in this directions have actually been provided by different authors. In particular, Fabbri (2003) estimates technical efficiency of all Italian public structures in a cross-sectional sample in 1999. Using Data Envelopment Analysis (DEA) the author find no significant regional differences in technical efficiency. At the same time, private not-for-profit (NFP) and large hospitals are the most productive ones. More recently, using DEA techniques on a sample of public Italian hospitals for the period 2000-2004 finds high heterogeneity in technical efficiency both within and between regions. Canta et al. (2005) are probably the only authors trying to estimate a cost frontier of public hospitals in Piedmont over the period from 2000 to 2004. They find evidence of a reduction in average cost inefficiency during the observed years and relevant scale economies not exploited by producers. However, their results should be taken with caution in that, as we previously noted, they were constrained to cost data aggregated mainly at LHA level.

Further results have also been provided by Barbetta et al. (2007) and Daidone and D'Amico (2009). The former study investigates behavioral differences between public and private nonprofit hospitals following the introduction of the DRG-based payment system. The latter research evaluate how the productive structure and level of specialization of the hospitals affect technical efficiency. The results obtained in these two articles cannot be entirely compared, since they cover a different time span and a different sample.

Despite the existence of substantial comparison problems, the results that stems from all these studies in

[2] By ownership status we mean the type of legal structure characterizing each hospital; by degree of capitalization we mean the combination of productive inputs, labor and capital, which defines the mix of offered services; finally, by degree of specialization we mean how concentrated are hospitals in terms of DRG performed.

terms of technical efficiency are substantially in line with those reported in **?** for the EU countries. However, this strand of the literature suffers from both data quality problems and, most importantly, from econometric problems. In particular, for what concerns data problems, it must be stressed that all these studies had either measurement error problems in the output variable (not accounting for case-mix and quality) or limitation on time (short panels) and space (only sub-samples of Italian hospitals at regional level) of the data-set. From the econometric side, estimates are likely to be inconsistent for cross-sectional studies, efficiency has always been estimated through second stage a approach (again inconsistently) and the statistical model adopted did not allow to obtain estimates that could distinguish between hospitals unobserved heterogeneity and inefficiency.

This last issue has represented the main drawback of the econometric literature on SF up to the seminal paper by Greene Greene (2005) who developped a model able to address the simultaneous presence of a time varying inefficiency term and a unit specific intercept. For this reason, Greene termed this model as "True" random or fixed effect model, depending on the nature of the unobserved heterogeneity (α_i). It must be stressed that introducing the "True" specification involves the solution of major computational and inferential problems. In fact, analogously to the cross-section case, in the panel specification we have to integrate out from the joint distribution of $(\boldsymbol{y}, \boldsymbol{u})$ the distribution of the inefficiency term $\boldsymbol{u}$ and this marginalization procedure generates a non linear panel data model, which carry some well known econometric problems.[3] In what follow our empirical analysis will take care of all these major problems that until now have pervaded the empirical literature in this field.

3 Methodology: the choice of the estimation strategy

A stochastic frontier (SF) model could be viewed as a regression model with a two-part error term in which the first one (i.i.d. and symmetric) represents the randomness component while the second (one-sided) represents inefficiency. As such, cost frontiers describe the minimum level of cost given output and input prices, while production frontiers represent the maximum amount of output that can be obtained from a given level of inputs. The distance between the observed output (or cost) and the estimated frontier, is interpreted as a measure of technical (or allocative) inefficiency.

A SF cannot be considered as model in which the inefficiencies are treated like the classical unobserved heterogeneity or a regression specification with an asymmetric error term because the measurement of inefficiencies and the estimation of the corresponding parameters are the key objectives of the analysis. Therefore, the specification and the estimation of the inefficiency distribution is a much more critical issue and the inefficiencies cannot be consider as a nuisance parameters.

Since the original work by Meeusen and van den Broeck (1977) and by Aigner et al. (1977), many reformulations and extensions have been proposed, using both frequentist and bayesian approaches.[4] In particular, the Bayesian approach has been firstly proposed by van den Broeck et al. (1994), and since then it became a rather popular choice in this field. In fact, even if in general there are nontrivial analytical and computational costs in adopting the Bayesian approach (due to the elicitation of the prior), in the SF case it allows to estimate the full inefficiency distribution, as opposed to the frequentist approach which relies on an approximation of the efficiencies represented by a (usually biased) estimate of the conditional mean of technical efficiency Jondrow et al. (1982). Furthermore, the Bayesian paradigm in the SF case leads to exact finite sample properties.

In terms of model specification, and until the contribution by Greene (2005), all parametric SF panel data models suffered from a major shortcoming (under both the frequentist and Bayesian approach): they do not allow a cross-sectional specific intercept to exist jointly with a time varying inefficiency term, providing no mechanism to disentangle unmeasured time invariant heterogeneity from inefficiency. In fact, time invariant omitted variables were likely to be captured by the inefficiency term, producing biased results in terms of efficiency measures and eventually wrong policy actions. Moreover, a time invariant inefficiency distribution clearly remains a questionable convenient assumption, especially in presence of long panels.

Within the frequentist approach, Greene (2005) has been the first to formally highlight this problem and to propose an econometric specification able to distinguish individual heterogeneity and time variant inefficiency. This new model, termed by the author as "true" random or fixed effects (according to the

[3]For an introduction of the literature of non linear panel data model, see Ch.23 of Cameron and Trivedi (2005). An alternative and more advanced source is represented by Chernozhukov et al. (2007).

[4]See Kumbhakar and Lovell (2000) or Greene (2008) for recent surveys.

nature of the individual effects), allows to perfectly separate the inefficiency component from the unit specific unobserved heterogeneity. It must also be noted that the adoption of this new econometric specification come not free of costs. In fact, by introducing the "true" specification we have to face all major common estimation problems related to non linear panel data models (Cameron and Trivedi, 2007).

For the counterpart "true" random or fixed effects model in the Bayesian framework we should note that in Bayesian inference there is no distinction between fixed and random effect, but only between hierarchical and non-hierarchical models (McCulloch and Rossi (1994)). As pointed out by Koop et al. (1997) the distinguish feature of the two approaches is not the nature of the individual effect, which are both stochastic, but the a priori dependence structure between those effects.

Faced with the double choice between a frequentist vs. a Bayesian approach and with random vs. fixed effects models we have opted for a Bayesian estimation procedure of the Greene's "true" random effects model, implying a hierarchical prior specification in which the dependence structure between the individual effects is defined conditional on a set of common parameters. As for the frequentist counterpart, we assume independence between random effects and explanatory variables.

This choice is mainly motivated by the peculiar characteristics of the Italian hospitals data. In fact, we are aware of the existence of a large amount of heterogeneity between Italian hospitals that we believe could hardly be explained solely on the base of observable characteristics. At the same time, measurement errors are quite low, due to the administrative nature of the data we will use. In a panel framework this may imply large values for the variance of the unobserved components and inefficiency and small values for the variance of the idiosyncratic error. This may potentially lead to a high signal to noise ratio. In a recent paper, through an extensive Montecarlo exercise Atella et al. (2010) have shown that when the two signal-to-noise ratios are simultaneously high, practical identification of parameters in frequentist "true" random effects models becomes harder with the rate of convergence of the optimization procedure that drastically reduces. By adopting a Bayesian approach we are able to handle such extreme situations.

3.1 The econometric model

Consider the following specification for a stochastic frontier model with unobserved heterogeneity:

$$\begin{aligned} y_{it} &= \alpha_i + X_{it}^{'}\beta + \varepsilon_{it}, && (1)\\ \varepsilon_{it} &= v_{it} \pm u_{it} && (2)\\ \alpha_i &\sim N(\mu, \sigma_\alpha) && (3)\\ v_{it} &\sim N(0, \sigma_v) && (4)\\ u_{it} &\sim Exp(\lambda) \quad i = 1, \ldots, n, \;\; t = 1, \ldots, T_i. && (5) \end{aligned}$$

where, for each unit i, y_{it} represents the level of output (or cost), X_{it} is a vector of inputs, β's are technology parameters and α_i is the individual fixed unobservable effect.[5] The composite error term ε_{it} is the difference (or sum) of v_{it}, the classical measurement and specification error, and u_{it}, the characteristic one-side disturbance which represent inefficiency. Furthermore, we complete the set of hypotheses assuming that v_{it} and u_{it} are independent. The sign of the last term in (5) depends on whether the frontier describes costs (positive) or production (negative).

Loosely speaking, in the Bayesian philosophy the available information can be categorized into information obtained from the data through the likelihood function and other information obtained independently from the data incorporated in the prior. In order to produce inference on the unknown parameters, we have to combine the prior and the likelihood to produce the distribution of the observables conditional on the data and the prior. The Bayes theorem update the prior distribution with the sampling information coming from the likelihood producing the posterior distribution which synthesize data and prior information.

It is worth noting that the posterior is a high-dimensional distribution, so its moments contain all relevant information. The Bayesian standard practice is to report moments of the marginal distributions of parameters such as the posterior mean and posterior standard deviation. However, the SF is a complicated model so the moments cannot be analytically evaluated. Simulation methods represent a practical tool to construct the estimators. In fact, if we are able to simulate from the posterior distribution the simulated moments, they are consistent estimators of the theoretical counterparts.

What follows in this section can be summarized according to the following steps:

[5]Note that both y_{it} and X_{it} will usually involve logarithmic transformations of respectively outputs and input prices for cost frontiers and outputs and inputs for production frontiers.

1. formally derive the likelihood function;
2. elicit and discuss the prior distribution;
3. derive the posterior distribution and discuss the simulation technique to simulate from it.

Under the assumption that the inefficiency component is exponentially distributed and given the independence assumption, the joint density function $f(\boldsymbol{v}, \boldsymbol{u})$ is given by the product of the individual density functions

$$f(\boldsymbol{y}, \boldsymbol{u}|\boldsymbol{\alpha}, \boldsymbol{\beta}, \sigma_v^2, \sigma_\alpha^2, \lambda) = \prod_{i=1}^{n}\prod_{t=1}^{T_i} \frac{1}{\sqrt{2\pi\sigma_v^2}} \exp\left\{ -\frac{y_{it} - \alpha_i - \mathbf{x}_{it}^{'}\boldsymbol{\beta} + u_{it}}{2\sigma_v^2} \right\} \times \\ \times \lambda \exp\left\{ -\lambda u_{it} \right\}, \quad (6)$$

the likelihood function can be expressed, after marginalizing the relation 6 over u_{it}, as

$$L(\boldsymbol{\Theta}|\boldsymbol{y}) \propto \prod_{1=1}^{n}\prod_{t=1}^{T_i} \lambda \exp\left\{ \frac{\lambda^2\sigma_v^2}{2} + \lambda(y_{it} - \alpha_i - \mathbf{x}_{it}^{'}\boldsymbol{\beta}) \right\} \times \\ \times \int_0^{+\infty} \frac{1}{\sqrt{2\pi\sigma_v^2}} \exp\left\{ \frac{(y_{it} - m_{it})^2}{2\sigma_v^2} \right\} du_{it}, \quad (7)$$

where $m_{it} = y_{it} - \alpha_i - \mathbf{x}_{it}^{'}\boldsymbol{\beta} - \lambda\sigma_v^2$.

In order to build a Bayesian regression model, we have to define a set of priors on the unknown vector of parameters $\boldsymbol{\Theta} = (\boldsymbol{\alpha}, \mu, \sigma_\alpha^2, \boldsymbol{\beta}, \sigma_v^2, \lambda)$. In this work we assume the following prior structure

$$\begin{aligned} \pi(\boldsymbol{\Theta}) &= \pi(\boldsymbol{\alpha}, \mu, \sigma_\alpha^2, \boldsymbol{\beta}, \sigma_v^2, \lambda) \\ &= \pi(\boldsymbol{\alpha}|\mu, \sigma_\alpha^2)\pi(\mu)\pi(\sigma_\alpha^2)\pi(\boldsymbol{\beta})\pi(\sigma_v^2)\pi(\lambda) \end{aligned}$$

where all distributions on the right-hand side will be such to guarantee a proper posterior distribution. In particular, we assume: for $\boldsymbol{\beta}$ and μ normals priors, while for σ_v^2 and σ_α^2 an inverse gamma distribution.

In order to account for firms characteristics, we follow Koop et al. (1997) that parameterized the prior mean of the inefficiency distribution by replacing the common parameter λ with the expression $\exp(z_{it}^{'}\delta)$, where z_{it} are dummy variables and δ is a vector of parameters. As pointed out by van den Broeck et al. (1994), if we define efficiency as $r_{it} = \exp(-u_{it})$, we can adopt the prior distribution for $\psi_l = \exp(\delta_l)$ as

$$\pi(\psi_1|a_1) = Ga(a_1, -\ln(r^*)),$$

and

$$\pi(\psi_l) = Ga(a_l, b_l), \quad \forall l > 1$$

where r^* is the implied prior median efficiency. We can either set $a_l = b_l = 1$ or we shall complete the prior for the general gamma inefficiency distribution by $a_l, b_l \sim Ga(1, 1)$ which is centered (through the prior mean) over the value leading to the exponential distribution, and has a reasonable prior variance for a_l and b_l equal to unity.

As mentioned before, in the Bayesian paradigm the prior are updated with the information contained in the likelihood using the Bayes theorem. This procedure leads to the posterior distribution which is proportional to the product between priors $\pi(\boldsymbol{\Theta})$ and the likelihood $\pi(\boldsymbol{y}, \boldsymbol{u}|\boldsymbol{\Theta})$.

The proposed model leads to a posterior distribution that is analytically intractable since the likelihood function given in (7) is **complicated**.[6] In order to perform Bayesian inferential procedures, it is possible to avoid burdensome computations using Markov chain Monte Carlo (MCMC) methods.

We construct a Markov chain defined by conditional distributions of parameters. In this Markov chain, a Gibbs sampler, the random draws are made from each full-conditional posterior distribution. In order to reduce the computational burden of the sampler, we apply a data augmentation scheme (Tanner and Wong

[6] In the case of a Normal-Gamma model, the second term of the likelihood is a fractional moment of a truncated normal distribution and only in the case of an Erlang distribution for $\boldsymbol{u}$, the likelihood function is analytically tractable.

(1987)) to our model treating the inefficiencies unobservable random vector $\boldsymbol{u}$ as an unknown parameter vector to be estimated. Hence, the latent vector $\boldsymbol{u}$ is simulated alongside the model parameters from their full posterior distribution.

We consider the augmented likelihood (6), obtaining the corresponding posterior

$$\pi(\alpha, \mu, \sigma^{\mathbf{2}}_{\alpha}, \boldsymbol{\beta}, \sigma^{\mathbf{2}}_{\mathbf{v}}, \boldsymbol{\psi}|\mathbf{y}, \mathbf{u}) \propto \mathbf{f}(\mathbf{y}, \mathbf{u}|\alpha, \mu, \sigma^{\mathbf{2}}_{\alpha}, \boldsymbol{\beta}, \sigma^{\mathbf{2}}_{\mathbf{v}}, \boldsymbol{\psi})\pi(\boldsymbol{\alpha}|\mu, \sigma^{\mathbf{2}}_{\alpha})\pi(\mu)\pi(\sigma^{\mathbf{2}}_{\alpha})\pi(\boldsymbol{\beta})\pi(\sigma^{\mathbf{2}}_{\mathbf{v}})\pi(\boldsymbol{\psi}) \tag{8}$$

The equation (8) has not a known distribution, but the Gibbs sampler is constructed by a sequential sampling of $\boldsymbol{\alpha}$, μ, σ^2_{α}, $\boldsymbol{\beta}$, σ^2_v, $\boldsymbol{\psi}$ and $\boldsymbol{u}$ from their full conditional distributions which are easily tractable. The derivation of the full-conditionals is straightforward so that the model update' rules are an adaptation of the formulae proposed in Koop et al. (1997) and in Chib and Carlin (1998).

4 Data

Our empirical analysis is based on administrative data provided by the Italian Ministry of Health and consist of hospital discharge records (HDRs) at patient level, and DRG weights (i.e. the level of complexity), by DRG and MDC specialty, physical equipment and machineries in use, number of beds and personnel at hospital level. All data are available over the period 1999-2007.

As hospitals are obliged by law to fill out HDR as informative tool over which to base hospital financing, this guarantee a high quality of the data. In each HDR, several data describing patient characteristics are recorded. Beyond vital statistics, we observe health-related information collected during the patient's internment such as date of admission, date of discharge and the like. Further, we observe the DRG related to each patient and its weight. Compared to existing literature on on hospital efficiency, this richness of information at patient level represents an innovation as it allows not only to capture the precise number of treated cases, but also to provide a measure of case-mix control for the output variable.

As far as the measurement of output is concerned, we have restricted our focus to acute care, which refers to the necessary treatment of a disease for a brief but severe episode of illness. The rationale of this choice is given by the fact that frontier techniques seem to work best when the product is homogeneous and one-dimensional, which is not the case for hospital care, which exhibits wide variation in the quality of the product and its dimensionality. Indeed, acute patients differ from long-term care and rehabilitation care patients, who receive a peculiar combination of treatments once the acute phase of the disease has been overcome. Hospitals devoting their activity exclusively to long-term and/or rehabilitation care, therefore, might not share the same technology with acute-care hospitals, which would make the two groups impossible to compare. For those hospitals dedicated only partially to post-acute care, we did not include the DRG weights from post-acute care activities in any of the output aggregates.

By limiting hospital activity to the treatment of acute patients, as measure of output we preferred inpatient discharges to inpatient days. In a prospective payment system the latter variable may reflect more a productive choice of the hospital management rather than patients' demand; hence it is more likely to be endogenous.[7]

Regarding the inputs, we use both the number of beds and a physical equipment and machinery index, as measures of capital and the number of physicians, nurses and other personnel as different measures of labor inputs. By classifying labor into different categories, we recognized differing skill requirements. We are aware that number of hours worked may be a better indicator of the labor factor, since it reveals more about the use of the workforce, but unfortunately such information is not available.

By exploiting the availability of detailed indicators about hospitals technical equipment, we construct a measure of capital by means of a composite indicator. In particular, we use a statistical approach based on factor analysis in which each hospital equipment indicator is weighted according to its contribution to the overall variance in the data.[8] Given that capital endowment is tightly related to hospital dimension, the composite machinery index was normalized using the number of beds.

As mentioned above when discussing the measure of output, some hospitals undertake both acute and post-acute care activity. Therefore, for consistency, we must net all input measures from that part that is not used for acute care. For the bed variable, this exclusion was straightforward, since we have data that distinguish acute care beds from rehabilitation and long-term care beds. However, hospital staff numbers

[7]See for instance Rosko and Broyles (1988).

[8]For more details see A.

were reported with no information on the type of care they provided. Therefore we constructed a simple measure of utilization, dividing the number of inpatient days for acute patients by the total number of inpatient days. This ratio was multiplied by each category of workers as an adjustment factor to obtain the measure of inputs used in the estimation.

Both public and private hospitals providing health care services are present in the sample. Public hospitals are financed by public funds, while both for-profit and not-for-profit hospitals rely on a mix of public and private funds. In order to compare productive units and make them as homogeneous as possible, we must control for differences in the source of funding. For this reason, in private hospitals, we consider only those services covered by public funds. In this way we are excluding those hospitals which did not sign any type of agreement with the National Health System (NHS) and are exclusively devoted to a "pure" private activity. For sake of consistency, in case of CCPA hospitals we consider only the number of beds accredited with the NHS and a proportional fraction of their personnel (i.e. the number of workers in each category multiplied by the share of beds in agreement with the NHS divided by the total number of beds).

Overall, hospital care in Italy is provided by a network of public hospitals, not-for-profit private hospitals and for-profit private hospitals (see also Appendix B). The total amount of hospitals operating in Italy has changed over our period of investigation, and it is a little bit larger than the actual number of hospitals we have in our dataset. This gives us a final sample of an unbalanced panel of 1,298 Italian hospitals observed over the period 1999-2007, which sums 9,186 observations. Table 1 shows the distribution of the hospitals and acute DRG weights per year, and by ownership structure. From the reading of input statistics (table 2), it appears private for-profit hospitals are smaller with respect to all size-related measures: fewer beds, personnel and lower index of machinery. Further, they are on average more specialized in specific major diagnostic categories, as it appears in the Gini index, which is obtained using the formula provided in Daidone and D'Amico (2009).

5 Empirical results

Our empirical analysis has been based on the estimation of a translog version of equation 1, where the presence of squared and interaction terms gives a high degree of flexibility. For what concern the technology parameter estimates, in addition to input variables, we include in the frontier:

- Time dummies for each year of the sample, using 1999 as the base year.
- Three variables concerning ownership: one dummy if the hospital is public and directly managed by LHA, a second dummy if the hospital is private not-for profit and a last one if the hospital is private for-profit. AO and PU represent represent the base category.
- Geographical dummies for each region.
- A Gini index of hospital specialization
- A dummy variable taking value equal to 1 whether the hospital is part of a region signing a bail-out plan.
- A dummy variable taking value equal to 1 whether the hospital is the result of a merge among different structures.

For the efficiency term we have instead included the following explanatory variables: three dummy variables referring to the second, third and fourth quartile of the index of specialization distribution (reference: the first quartile); two dummy variables for medium and high capital-labor ratio levels, defined as number of beds divided by the number of nurses (reference: low capital-labor ratio); four dummy variables for geographic areas, i.e. North-West, North-East, Center and South (reference: Islands); one dummy variable for belonging to one of the region having signed a bail-out plan.

Notice that within the bayesian framework we are able not only to produce estimates of parameters' coefficients, their standard errors and/or some linear combinations of them, but also their entire distribution. What we have reported in the following tables is a credibility or probability interval, not simply a confidence interval. The setting of the Markov-chain has been the following: we take 20,000 iterations, with a burn-in of initial 5,000 iterations. In order to avoid problems of serial autocorrelation in the chain, we set the thinning at 5. Finally, it must be highlighted that in a Bayesian context, as a rule of thumb, when the estimated mean and the median of the parameters or elasticities tend to be very close, it can be interpreted as a good sign that the chain for those parameters converged.

5.1 Technology parameter results

In table 3 we show scale and input elasticities, which are more meaningful than the simple technology parameters in a translog function context. Elasticities have been estimated at the means of the variables in the data. By simple comparison of estimates at the mean and the median we observe that coefficients are substantially equal up to the second digit, thus proving that the chain has correctly converged. From an economic perspective the parameter estimates suggest significant decreasing returns to scale, since scale elasticities $\epsilon_{\mathbf{y},\mathbf{x}} < 1$ and the hypothesis of constant returns to scale is rejected (the scale elasticity has a 99% probability of being included in the interval 0.6707-0.8831). From a policy perspective, this seems to suggest that there is an incentive to decentralize operations.

The individual input elasticities underlying the scale elasticities are also provided. Elasticities for all personnel groups are low and close to 0, while the **marginal product** of the two capital measures is much higher, especially for beds, which has been estimated very precisely (witha credibility interval between 0.3012 and 0.3602). Therefore it seems there is some excess in the size for all group of workers, especially for the residual category.

In table 4 we report the estimates of all parameters of our hybrid Translog production function. Coherently with what anticipated in section 3, it is worth stressing that the estimated variance parameters produce extremely high signal-to-noise ratios, i.e. $\frac{\sigma_\alpha}{\sigma_v} \approx 113$ and $\frac{\sigma_u}{\sigma_v} \approx 52$. According to Atella et al. (2010), in a frequentist approach identification of parameters and convergence of the maximization procedure starts to become a problem with signal-to-noise ratios above 25. This results represents the best evidence that our strategy in using a Bayesian approach to estimate a model that allows to disentangle efficiency from unobserved heterogeneity was the correct one.[9]

As far as the frontier parameters are concerned, time dummies point out a moderate positive time trend until 2005, which is followed by a negative trend in the production of adjusted discharges. This result is specular to the reading of the descriptive statistics shown in table 1(b). The Gini coefficient is negative and "significant", indicating that higher hospital specialization is correlated with lower discharge rates. Further the dummy for hospital mergers is positive and the magnitude is high, an evidence that organizational restructuring positively contributed to the overall output. Finally the coefficient on the dummy for the bail-out plan is also positive but the impact appears negligible, even if statistically different from 0. The rationale is that these plans were signed only in 2006 for the aforementioned subset of regions with health deficits, so that it is possible that the effects will be more marked in the following years, which are not part of our sample.

5.2 Efficiency parameter results

With respect to inefficiency effects, table 5 shows that increasing specialization reduces efficiency, since the magnitude on the dummies for higher quartiles is increasingly larger in absolute terms. Evidence is not straightforward for the capital-labor ratio, in that medium levels are not different from low levels of capitalization in terms of efficiency, while high levels are significantly negative. Finally the coefficient on the bail-out plans indicate that probably higher levels of productions were achieved at the cost of producing less efficiently, overall considering that the number of inputs did not reduce at all.

As reported in table 6 and according to what we just said, average efficiency score decreases as the Gini index increases and when more capitalized hospitals are considered. As might be expected, productive structure is strictly related to efficiency scores. While there is no specific trend regardless of the ownership structure in the observed period. Table 7 shows that, on average, a public hospital is 15% more efficient than a private not-for-profit one. This relation is partially driven by the fact that hospitals appear to be more capitalized and specialized moving from a public to a private ownership. This result supports the evidence that specialization could be achieved only at the cost of a departure from the efficient frontier.

[9] As counterfactual we have also estimated the frequentist counterpart of "true" random effect model, but as expected the likelihood function did not converge to a maximum. Results are available upon request.

6 Conclusions

The main goal of this work has been to assess evolution of technical efficiency in a large longitudinal database of Italian hospitals over the period 1999-2007 by means of a parametric analysis based on stochastic frontier approach. Compared to existing literature we have improved under different aspects. First of all, from a methodological perspective, we have for the first time in this sector implemented a “true” random effects estimator and have jointly estimated the technology and the inefficiency equations. This approach has allowed *i)* to disentangle cross hospital unobserved heterogeneity from hospital inefficient behavior and *ii)* to provide more precise estimates of both technology and efficiency. Second, estimates have been obtained using a *Bayesian* stochastic frontier technique that seems to be more suitable to identify parameters when unobserved heterogeneity and inefficiency are jointly estimated. Third, for the first time we try to evaluate to which extent the set of national and regional cost control policies implemented over our period of investigation and the bail-out programs signed with specific regions have affected hospital efficiency. Finally, we improve with respect to previous empirical studies on Italian hospitals as we are able to obtain a better measure of output, a much longer time period and a much larger number of hospitals that have allowed to carry out technical efficiency comparison by regional macro-areas.

Results shows some changes in the technical efficiency of hospitals over time and the existence of non negligible level of heterogeneity by ownership status. Furthermore, we find that specialization decrease inefficiency, which seems to have increased in the last years, especially in the regions with bail-out plans.

References

Aigner, D., C. Lovell, and P. Schmidt. 1977. Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics* 6(1): 21–37.

Atella, V., F. Belotti, S. Daidone, and G. Ilardi. 2010. Some practical considerations on identification and inference in stochastic frontier models with unobserved heterogeneity. Mimeo.

Barbetta, G., G. Turati, and A. Zago. 2007. Behavioral differences between public and private not-for-profit hospitals in the Italian national health service. *Health Economics* 16: 75–96.

van den Broeck, J., G. Koop, J. Osiewalski, and M. Steel. 1994. Stochastic Frontier Models: A Bayesian Perspective. *Journal of Econometrics* 61: 273–303.

Cameron, A., and P. Trivedi. 2005. *Microeconometrics: Methods and applications.* Cambridge University Press.

Canta, C., M. Piacenza, and G. Turati. 2005. Riforme del Servizio Sanitario Nazionale e dinamica dell'efficienza ospedaliera in Piemonte. *CERIS Working Paper* Institute for Economic Research on Firms and Growth(200515).

Chernozhukov, V., I. Fernandez-Val, J. Hahn, and W. Newey. 2007. Identification and estimation of marginal effects in nonlinear panel models.

Chib, S., and B. P. Carlin. 1998. On MCMC Sampling in Hierarchical Longitudinal Models. *Statistics and Computing* 9: 17–26.

Daidone, S., and F. D'Amico. 2009. Technical efficiency, specialization and ownership form: Evidences from a pooling of Italian hospitals. *Journal of Productivity Analysis* 32: 203–216.

Fabbri, D. 2003. *L'efficienza dei servizi pubblici*, chap. L'efficienza tecnica e di scala degli ospedali pubblici in Italia. Banca D'Italia.

Greene, W. 2005. Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. *Journal of Econometrics* 126: 269–303.

———. 2008. *The Measurement of Efficiency*, chap. The Econometric Approach to Efficiency Analysis. Oxford University Press.

Jondrow, J., C. Lovell, I. Materov, and P. Schmidt. 1982. On the estimation of technical efficiency in the stochastic production function model. *Journal of Econometrics* 19: 233–238.

Koop, G., J. Osiewalski, and M. Steel. 1997. Bayesian efficiency analysis through individual effects: hospital cost frontiers. *Journal of Econometrics* 76: 77105.

Kumbhakar, S., and C. Lovell. 2000. *Stochastic frontier analysis.* Cambridge University Press.

McCulloch, R., and P. Rossi. 1994. An Exact Likelihood Analysis of the Multinomial Probit Model. *Journal of Econometrics* 64: 207–240.

Meeusen, W., and J. van den Broeck. 1977. Efficiency estimation from Cobb-Douglas production function with composed errors. *International Economic Review* 18(2): 435–444.

Nardo, M., M. Saisana, A. Saltelli, S. Tarantola, A. Hoffman, and E. Giovannini. 2005. Handbook on Constructing Composite Indicators: Methodology and User Guide. Technical Report 3, OECD, Paris.

Nicoletti, G., S. Scarpetta, and O. Boylaud. 2001. Summary Indicators of Product Market Regulation with an Extension to Employment Protection Legislation. *OECD Economics Department Working Papers* (226).

RGS. 1994. *Relazione Generale sulla Situazione Economica del Paese*, chap. Le Analisi. Ministry of Economics and Finance.

———. 2010. *Relazione Generale sulla Situazione Economica del Paese*, chap. Le Analisi. Ministry of Economics and Finance.

Rosko, M., and R. Broyles. 1988. *The economics of healthcare: a reference handbook.* Westport, CT: Greenwood Press Inc.

Tanner, M., and W. Wong. 1987. The calculation of posterior distributions by data augmentation (with discussion). *Journal of the American Statistical Association* 82: 528–550.

A Appendix - The physical equipment index

The composite machinery indicator used in this paper is built upon the OECD methodology described in Nardo et al. (2005). Following a statistical approach based on factor analysis, each hospital equipment indicator is weighted according to its contribution to the overall variance in the data. Factor analysis basically reveals groups of detailed technical equipment indicators which are most associated with different underlying (unobserved) factors. Each factor is defined as a set of coefficients, so-called loadings, each measuring the correlation between the individual indicators and the latent factor. Principal component analysis was used to extract the factors.

Each factor contributes to a different extent to the explanation of the overall cross-hospital variance and it is usually sufficient to focus only on a few factors whose combined contributions explain a significant proportion of this variance. To maximize the variance of the data explained by each factor, we select factors with eigenvalue greater than 1, each of which explains at least 10% of the observed variance and so that the explained cumulative variance is greater than 80%.

After rotating the factors, mainly to ensure that each equipment indicator is "loaded" exclusively on one of the retained factors, the final step involves the construction of the set of weights. Rotation is a standard step in factor analysis (see for instance Kline, 1994). It changes the factor loadings and consequently the interpretation of the factors while factor analytical solutions remain mathematically equivalent in that they explain the same portion of the sample variance. Among different rotation methods, we use *varimax* which basically attempts to minimize the number of variables having high loadings on a factor. Following Nicoletti et al. (2001) each detailed indicator is weighted according to the normalized squared loading (i.e. the proportion of the variance explained by the factor is associated to). The resulting intermediate indicators are then combined according to the normalized sum of squared loadings (i.e. the contribution of each factor to the total explained variance).

B Appendix - The secondary care hospital sector in Italy

In this appendix we report some information on the institutional organization of secondary care providers in Italy. Secondary care in Italy is provided by public hospitals, not-for-profit private hospitals and for-profit private hospitals. For public hospitals, here below we report a classification that has recently been adopted by the Ministry of Health:

- *Aziende Ospedaliere* (AOs). AOs are independent public providers characterized by peculiar organizational, administrative, financial and accounting freedom (D.Lgs. 502/92). In particular, AOs must organize wards into departments; they must produce financial accounts and income and expenditure accounts; they must have at least three highly specialized wards and a II-level A&E department; they must provide secondary care to all NHS patients, regardless of their residence; they must provide elective inpatient care; they must have a case-mix index 20% higher than the average regional case-mix; they must break-even; in case of surpluses, they can re-invest them; in case of losses, they immediately loose their independence. When established in 1992, AOs' were mostly funded by Regions (80% of the historical costs, less the eventual surplus), that also commission care on behalf of the resident population. Acute inpatient and outpatient care is thus agreed in advance between AOs and the Regions, taking into account population's needs and the tariff for the reimbursement. The remaining 20% of total costs was paid through a fixed tariff. Nowadays, all AOs are paid for volumes of work adjusted for differences in case-mix.

- *Aziende Ospedaliere Universitarie e Policlinici Pubblici* (public AOU&POLIs). Public AOU&POLIs are independent public hospitals characterized by peculiar organizational, administrative, financial and accounting freedom (following the legislative decree 502/92) with a twofold mission: to provide health care to patients according to the NHS standards and to provide higher education to medical students (Law 833/78).

- *Istituti di Ricovero e Cura a Carattere Scientifico e Fondazioni Pubbliche* (public IRCCS). Public IRCCS are particular public hospitals that offer secondary care services and that also carry on medical and bio-medical advanced research, both with very high standards of excellence. Such hospitals are supposed to perfectly integrate scientific research, education and care of patients (L.833/78).

- *Ospedali a Gestione Diretta Presidio della ASL* (OGDs). OGDs are public providers characterized by organizational and administrative AOs, but they are directly under LHAs' control and therefore with limited financial and accounting freedom (Legislative decree 502/92).

For not-for-profit private hospitals, the Ministry of Health has adopted the following classification:

- *Policlinici Privati* (private POLIs). Private POLIs have the same characteristics as public ones but they are privately owned.

- *Istituti di Ricovero e Cura a Carattere Scientifico e Fondazioni Private* (private IRCCS). Private IRCCS have the same characteristics as public ones but they are privately owned.

- *Ospedali Classificati* (OCs). OCs are private providers generally owned by religious groups and authorized to provide secondary care services in accordance to the Italian legislation (Law 833/78).

- *Istituti Privati Qualificati Presidio della ASL* (IASLs). IASLs have the same characteristics of OGDs, but they are privately owned (L. 833/78).

- *Enti di ricerca* (ERs). ERs are private research and care centers endowed with specialized medical staff and medical equipment and assimilated to public AOU&POLIs (Law 833/78).

- *Case di Cura Private Accreditate* (CCPAs). As public hospitals, CCPAs are private owned structures, fully or partially accredited, that offer free to the point of use services, in accordance to NHS standards.

Finally, regarding for-profit private hospitals, the Ministry of Health has adopted the following classification:

- *Case di Cura Private Non Accreditate* (CCPNA). CCPNAs are fully private providers that offer secondary care services.

In order to have homogeneous groups of hospitals with similar characteristics and equivalent ownership status, we have grouped our hospitals according to the following aggregate categorization:
Group 1: AOs, AOU & POLIs, Public IRCCS
Group 2: ODGs
Group 3: Private POLIs, Private IRCSS, OCs, IASLs, ERs
Group 4: CCPAs
Finally, CCPNAs have not been included in the analysis as we do not have information on output data.

Tables

Table 1: Number of hospitals and acute DRG weights by year and ownership type

(a) Hospitals

Year	AO	PUB	NFP	PFP	Total
1999	92	500	31	364	987
2000	96	511	41	382	1,030
2001	98	510	41	398	1,047
2002	99	509	41	413	1,062
2003	92	465	40	413	1,010
2004	117	433	51	419	1,020
2005	116	432	54	417	1,019
2006	118	416	56	416	1,006
2007	117	416	65	407	1,005
Total	945	4,192	420	3,629	9,186

(b) Acute DRG weights

Year	AO	PUB	NFP	PFP	Total
1999	3,835,711	4,630,701	345,894	1,196,190	10,008,497
2000	4,128,424	4,911,723	437,893	1,339,924	10,817,963
2001	4,297,552	4,984,434	472,252	1,469,323	11,223,562
2002	4,372,149	4,981,222	490,684	1,598,497	11,442,552
2003	4,141,623	5,068,011	478,138	1,625,017	11,312,789
2004	4,887,887	5,202,251	826,515	1,756,763	12,673,417
2005	4,925,790	5,264,423	895,719	1,800,311	12,886,244
2006	4,348,210	4,514,011	840,887	1,640,171	11,343,280
2007	4,070,519	4,366,560	1,203,054	1,517,782	11,157,916
Total	39,007,865	43,923,338	5,991,037	13,943,979	102,866,219

Table 2: Descriptive statistics on inputs by ownership type

	Physicians	**Nurses**	**Other staff**	**Beds**	**Machinery**	**Gini**
AO	391	910	892	808	5.3846	0.5357
	(240)	(590)	(611)	(484)	(0.3486)	(0.1191)
PUB	100	249	182	232	5.2008	0.6040
	(92)	(239)	(179)	(207)	(0.3972)	(0.0991)
NFP	117	238	268	276	5.2808	0.6592
	(102)	(229)	(250)	(204)	(0.3910)	(0.1249)
PFP	36	47	66	102	5.1665	0.7808
	(33)	(50)	(62)	(75)	(0.6122)	(0.1033)
Total	105	236	213	242	5.2098	0.6693
	(145)	(355)	(337)	(297)	(0.4936)	(0.1399)

Notes: standard deviations in parentheses

Table 3: Elasticities

	Mean	Median	p0.5	p2.5	p97.5	p99.5
ϵ_{phys}	0.1090	0.1091	0.0878	0.0927	0.1257	0.1305
ϵ_{nurse}	0.1084	0.1083	0.0838	0.0895	0.1278	0.1335
ϵ_{oth}	0.0560	0.0560	0.0364	0.0412	0.0708	0.0757
ϵ_{mach}	0.1707	0.1709	0.0736	0.0968	0.2451	0.2697
ϵ_{beds}	0.3311	0.3311	0.3012	0.3087	0.3533	0.3602
ϵ_{scale}	0.7753	0.7750	0.6707	0.6948	0.8559	0.8831

Table 4: Other frontier parameters

	Mean	Median	p0.5	p2.5	p97.5	p99.5
V.Aosta	0.5399	0.5193	-0.8389	-0.6389	1.8747	2.1798
Lombardia	0.2303	0.2297	-0.0187	0.0259	0.4421	0.4902
Bolzano	0.0075	0.0088	-0.5350	-0.4347	0.5049	0.5902
Trento	-0.1067	-0.1013	-0.6353	-0.5204	0.2559	0.4538
Veneto	0.1100	0.1058	-0.1472	-0.0881	0.3269	0.4118
Friuli	0.0599	0.0644	-0.3015	-0.2166	0.3327	0.4366
Liguria	0.3528	0.3468	-0.0089	0.0594	0.6454	0.7183
Emilia	0.0851	0.0807	-0.1914	-0.1299	0.3150	0.3729
Toscana	0.2386	0.2275	-0.0326	0.0088	0.5573	0.6222
Umbria	0.3893	0.3972	-0.0939	-0.0110	0.7325	0.8800
Marche	-0.0070	-0.0119	-0.2741	-0.2246	0.2653	0.3721
Lazio	-0.0528	-0.0571	-0.2449	-0.2166	0.1847	0.2455
Abruzzo	0.3831	0.3790	0.0950	0.1679	0.6311	0.7800
Molise	0.2161	0.1842	-0.2683	-0.1800	0.8269	1.0003
Campania	0.2890	0.2899	0.0569	0.1004	0.5456	0.6245
Puglia	0.1864	0.1879	-0.0594	-0.0137	0.4029	0.4932
Basilicata	0.0118	0.0026	-0.4936	-0.3895	0.4305	0.5380
Calabria	-0.0263	-0.0246	-0.3298	-0.2586	0.1882	0.2690
Sicilia	0.3094	0.3088	0.0752	0.1292	0.4980	0.5695
Sardegna	0.0483	0.0409	-0.2462	-0.1832	0.3080	0.4366
2000	0.0033	0.0033	-0.0096	-0.0067	0.0133	0.0163
2001	0.0166	0.0166	0.0029	0.0064	0.0268	0.0300
2002	0.0214	0.0215	0.0080	0.0110	0.0319	0.0353
2003	0.0259	0.0259	0.0113	0.0147	0.0372	0.0408
2004	0.0717	0.0717	0.0568	0.0603	0.0829	0.0866
2005	0.0851	0.0851	0.0702	0.0733	0.0968	0.1006
2006	-0.0354	-0.0353	-0.0512	-0.0472	-0.0235	-0.0198
2007	-0.0471	-0.0472	-0.0647	-0.0603	-0.0336	-0.0296
Gini	-1.0190	-1.0187	-1.2108	-1.1735	-0.8661	-0.7871
Pub	-0.1843	-0.1845	-0.2877	-0.2636	-0.1065	-0.0824
NFP	-0.0771	-0.0778	-0.1906	-0.1602	0.0096	0.0348
PrivFP	-0.4333	-0.4343	-0.5623	-0.5321	-0.3285	-0.2910
Bailout-plan	0.0331	0.0330	0.0052	0.0117	0.0556	0.0628
Merge	0.4553	0.4557	0.2323	0.3071	0.6119	0.6698
μ	0.4961	0.4996	0.1389	0.1814	0.7272	0.7518
σ_α	0.3952	0.3946	0.3445	0.3563	0.4373	0.4532
σ_v	0.0035	0.0035	0.0031	0.0032	0.0039	0.0041

Table 5: Mean of U

	Mean	Median	p0.5	p2.5	p97.5	p99.5
Constant	2.5095	2.5096	2.3830	2.4135	2.6047	2.6352
2nd-Quartile-Gini	-0.5657	-0.5659	-0.6766	-0.6487	-0.4835	-0.4599
3rd-Quartile-Gini	-1.0182	-1.0182	-1.1330	-1.1065	-0.9296	-0.9013
4th-Quartile-Gini	-1.1843	-1.1845	-1.3037	-1.2748	-1.0914	-1.0629
KLInd2	0.0644	0.0644	-0.0254	-0.0029	0.1325	0.1535
KLInd3	-0.3851	-0.3848	-0.4856	-0.4611	-0.3093	-0.2859
NO	0.0981	0.0982	-0.0261	0.0040	0.1937	0.2208
NE	0.1930	0.1934	0.0639	0.0947	0.2904	0.3203
C	0.0687	0.0687	-0.0479	-0.0197	0.1581	0.1888
Sud	0.1631	0.1634	0.0559	0.0808	0.2456	0.2717
Bailout-plan	-0.3248	-0.3246	-0.5145	-0.4716	-0.1814	-0.1332

Table 6: Inefficiency estimate by specialization and capitalization

Gini	**Capital labor ratio**			
quartiles	Low	medium	High	Total
1st	0.933	0.934	0.864	0.932
2nd	0.889	0.897	0.813	0.882
3rd	0.817	0.854	0.782	0.810
4th	0.801	0.799	0.761	0.774
Total	0.891	0.881	0.776	0.849

Table 7: Inefficiency estimate by ownership structure and year

	Ownership structure			
Year	**AO**	**PUB**	**NFP**	**PFP**
1999	0.906	0.877	0.809	0.746
2000	0.920	0.889	0.826	0.776
2001	0.931	0.894	0.866	0.782
2002	0.945	0.892	0.871	0.801
2003	0.934	0.893	0.855	0.797
2004	0.926	0.894	0.892	0.799
2005	0.930	0.890	0.886	0.822
2006	0.922	0.872	0.867	0.806
2007	0.913	0.842	0.853	0.768
Total	0.925	0.883	0.861	0.789