UNIVERSITA' DEGLI STUDI DI ROMA "TOR VERGATA"
FACOLTA' DI ECONOMIA

Dottorato di ricerca in Econometria ed Economia Empirica
XXI ciclo

Essays in Health Economics and in Development

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Dedico questa tesi di dottorato a mia moglie, Ruth,
che ha avuto il coraggio di attraversare un oceano
e la pazienza di resistere a stupide burocrazie
pur di starmi accanto e seguirmi in questa nostra avventura.

Ringrazio mia madre, mio padre, fratè,
nonna Gina, la zia Gnommera e zio Al
che non hanno mai mancato di darmi
il loro affetto e supporto.

Non posso fare a meno di ricordare
i miei amici del dottorato,
con cui ho condiviso gioie e dolori di questi anni:
Alberto, Andrei, Ery, Fede, Frank, Peppe & Peppe, Mimmo,
e gli altri compagni da me qui non menzionati.

Vorrei ringraziare inoltre Vincenzo Atella, Gustavo Anríquez
e Laurence Baker per i loro insegnamenti, il tempo dedicato e la disponibilità.

Infine mi auguro di poter rivedere presto
il sorriso dei miei nipoti, dei cognati, de las tias
e di tutti coloro che durante la mia esperienza negli Stati Uniti
mi hanno fatto sentire a casa, felice.

Abstract

How is medical technology affecting costs growth? Evidence from a panel of US hospitals

In this paper we assess quantitatively the impact of technology on US hospital costs. American Hospital Association (AHA) surveys allow to identify the availability of technologies, while Medicare Cost reports provide us financial information. We define a novel index of equipment, procedures and processes availability that enables us to circumvent the assumption of innovations equally spread over all hospitals. By means of a simple dummy variables approach we are able to identify both innovations that are either cost pushing or cost-saving and the time pattern of these effects. Overall our estimates confirm the common knowledge that technology is severely rising hospital costs.

Ten years of DRG reform. An empirical analysis of the influence of specialization, productive structure and ownership form on Italian hospitals technical efficiency.

We evaluate how the productive structure and level of specialization of a hospital affect technical efficiency by analyzing a six-year panel database (2000/2005) drawn from hospital discharge records and Ministry of Health data. We adopt a distance function approach, while measuring the technical efficiency level with stochastic frontier techniques. After controlling for environmental variables and hospital case-mix, inefficiency is negatively associated with specialization and positively associated with capitalization. Capitalization is typical of private structures which, on average, use resources less efficiently with respect to public and not-for-profit hospitals. Finally, by looking at scale elasticities, we find some evidence of unexploited economies of scale, leaving room for centralization.

Within households effects of expanding rural nonfarm sector in a developing country.

This article explores the effects within households of an expanding rural nonfarm (RNF) sector in Ghana. We ask whether the growing RNF sector allows for economies of diversification within farms and how it affects household input demands. We explore the intrahousehold linkages between agricultural and RNF activities, first assuming perfectly competitive input and output markets and then with market failures, in particular missing labor and credit markets. We then measure these linkages using a household level input distance function, finding high levels of inefficiency in Ghanaian farms. Also, there are cost-complementarities between the RNF sector and the agricultural sector, particularly with food crops in which the poorest tend to specialize. The expansion of the RNF sector increases demand for most inputs including agricultural land.

Keywords: Technology index, Hospitals, Cost functions. Stochastic frontiers, Hospital Discharge Records, Hospital Specialization, Distance Functions, Technical efficiency. Rural nonfarm sector, Cost complementarities, Ghana.

Abstract

How is medical technology affecting costs growth? Evidence from a panel of US hospitals.

In questo articolo misuriamo l'impatto dell'innovazione tecnologica sui costi degli ospedali statunitensi. Le indagini campionarie dell'American Hospital Association (AHA) ci permettono di identificare la disponibilità di determinate tecnologie all'interno dei singoli ospedali, mentre dai rapporti di costo di Medicare reperiamo i dati di natura finanziaria. Definiamo un nuovo indice di disponibilità di macchinari, procedure e processi che permette di evitare l'assunzione di innovazioni tecnologiche egualmente distribuite fra tutti gli ospedali. Per mezzo di un semplice modello di variabili binarie, siamo in grado di identificare sia quelle innovazioni che provocano una riduzione o un incremento dei costi sia lo sviluppo temporale di tali effetti. Complessivamente le nostre stime confermano un fatto generale di publico dominio, che la tecnologia sta comportando un notevole aumento dei costi ospedalieri.

Ten years of DRG reform. An empirical analysis of the influence of specialization, productive structure and ownership form on italian hospitals technical efficiency.

In questo articolo studiamo come struttura produttiva e specializzazione influiscano sull'efficienza tecnica degli ospedali della regione Lazio, attraverso l'analisi di un campione longitudinale di durata pari a sei anni (2000/2005) derivato dalle schede di dimissione ospedaliera e dalla banca dati del Ministero della Salute. Adottiamo un approccio di funzioni distanza, implementato con tecniche di frontiere stocastiche atte a misurare il livello di efficienza tecnica. Dopo aver controllato per fattori "ambientali" e complessità ospedaliera, osserviamo che l'inefficienza è negativamente associata con il grado di specializzazione e positivamente con quello di capitalizzazione. Il più elevato rapporto capitale-lavoro risulta essere tipico delle strutture private, le quali in media fanno un uso meno efficiente delle risorse a loro disposizione rispetto agli ospedali pubblici e a quelli a loro assimilati. Infine, l'analisi delle elasticità di scala mette in evidenza la presenza di economie di scala non sfruttate, che sembra suggerire un intervento di centralizzazione/ristrutturazione delle operazioni.

Within households effects of expanding rural nonfarm sector in a developing country.

Questo articolo studia gli effetti all'interno delle famiglie dell'espansione del settore non agricolo rurale (RNF) in Ghana. Ci domandiamo se la crescita del settore RNF permetta economie di diversificazione/scopo all'interno delle aziende agricole e come questo influisca sulla domanda di input delle famiglie. Studiamo le connessioni all'interno delle famiglie tra attività agricole e non agricole rurali, dapprima assumendo mercati degli input e degli output perfettamente concorrenziali, e in secondo luogo ipotizzando fallimenti di mercato, in particolare del mercato del lavoro e del credito. Misuriamo queste connessioni attraverso una funzione distanza orientata agli input a livello delle famiglie. Esistono forti complementarietà di costo tra il settore agricolo e non agricolo rurale, soprattutto per le colture da sussistenza, nelle quali le famiglie più povere tendono a specializzarsi. L'espansione del settore RNF aumenta la domanda per la maggior parte degli input, incluso il fattore terra a scopi agricoli.

Keywords: Indice di tecnologia, Ospedali, Funzioni di costo. Frontiere stocastiche, Schede di dimissione ospedaliera, Specializzazione ospedaliera, Funzioni distanza, Efficienza Tecnica. Settore non agricolo rurale, Complementarietà di costo, Ghana.

Contents

How is medical technology affecting costs growth? Evidence from a panel of US hospitals.[1]

Abstract

In this paper we assess quantitatively the impact of technology on US hospital costs. American Hospital Association (AHA) surveys allow to identify the availability of technologies, while Medicare Cost reports provide us financial information. We define a novel index of equipment, procedures and processes availability that enables us to circumvent the assumption of innovations equally spread over all hospitals. By means of a simple dummy variables approach we are able to identify both innovations that are either cost pushing or cost-saving and the time pattern of these effects. Overall our estimates confirm the common knowledge that technology is severely rising hospital costs.

Keywords: Technology index, Hospitals, Cost functions.

[1] This chapter is based on "The butler is always the killer: Reassessing the impact of technology on hospital costs growth." by S.Daidone and L. Baker. We thank Jay Bhattacharaya, Daniel Kessler, Kate Bundorf and Federico Belotti for their suggestions. Corresponding author: Silvio Daidone, University of Rome Tor Vergata, Viale Columbia, 2 00133 Roma, Italy. E-mail: `silvio.daidone@uniroma2.it`.

1.1 Introduction

Health care bill continues to grow very rapidly in the US. Since 1970, health expenses have grown at an average annual rate of 9.6%, which is about 2.4 percentage points faster than the economy as measured by the nominal GDP. Annual spending on health care increased from $75 billion in 1970 to $2.2 trillion in 2007. As a share of the economy, health care has more than doubled over the past 40 years, rising from 7.2% of GDP in 1970 to 16.2% in 2007. A central issue from policymakers' viewpoint is why spending on health care steadily increases more quickly than spending on other goods and services. Health care economists pointed to the development and expansion of medical technology as primary factors in explaining the persistent growth of health care expenditures.[2]

In the literature a number of approaches have been employed to measure the effect of technology on health care costs. The most widely-used residual approach computes the effects of variations in factors such as consumption, prices, population growth and demographic changes. The residual is ascribed to variations in technology, thus avoiding to quantify explicitly technological progress. Nevertheless this approach suffers one major drawback: it is a coarse, indirect overestimation of the impact of technology. Determinants of health spending that are not accounted for or that cannot be quantified like environment, geography or lifestyle will also be considered as being technical change.

With the proxy approach, a variable such as research and development spending, or time is used to compute the impact of technology. The efficacy of these studies is related to the level of measurability and substitutability of the proxy for technology. Most of this kind of works simply add a time trend variable to the cost equation, thus assuming that technical change is Hicksian neutral or disembodied. Further, including a time trend variable also implies a continuous smooth process at a constant rate, which might not represent a realistic assumption.

Finally case studies evaluate the consequences of specific technologies on the costs of treating a precise medical condition. Despite being more accurate in explaining the impact of certain medical advances, it is tricky to generalize from them to an aggregate or national level.

Our aim with this paper is to assess quantitatively the impact of technology on hospital costs. We focus on hospital care expenditures for two reasons. First of all, hospital expenses still make up the major share of total health spending. After having reached a 40% peak in 1982, they have constantly declined in the 80s and 90s and stabilized in the last decade into a 31% level. Secondly, US hospital data, which are generally used for research purposes, provide good information on both the availability of a host of technologies and the level of costs.

With respect to previous literature we provide a set of three contributions. First, while most articles on hospitals efficiency and productivity concentrate on the effects of environmental pressures or on economic issues such as economies of scale/scope, we move our attention to the impact of

[2]See for instance Newhouse (1992) and Okunade, A.A. and V.N.R. Murthy (2002).

technology on costs. Technological developments are of great interest in the hospital industry, since they might be either cost shrinking or cost shifting. Second, we define a novel index of equipment, procedures and processes availability, which solve one big concern connected with the index of technology developed by Baker and Spetz (2002). This index enables us to circumvent the unpleasant assumption of innovations equally spread over all firms, i.e. hospitals in our study, avoiding the common practice in production economics to use time trends or dummies. Finally, by means of a simple alternative technology dummies approach we are able to identify not only which innovations push up or reduce costs, but also the time pattern of these effects.

The paper is organized as follows. Section 1.2 reports a short review of the literature. In section 1.3 we describe how we define and construct one hospital technology. Section 1.4 discusses the economic model and section 3.5 shows the data used for our analysis. Then in section 1.6 we present some results. We conclude by commenting on our findings.

1.2 The role of technology on hospital care spending: a short review of the literature

There is a large body of literature both on the impact of technology on health care spending and on the efficiency and productivity of hospitals. Much less interest is given to the effects of technological developments and innovation on hospital expenses. To our knowledge Davis (1974) is the first study on this issue. She applied a residual approach on a pooled cross-section of US non-profit private hospitals submitting audited cost data in the time span from 1962 to 1968. Her objective was to evaluate the relative importance of demand factors, case mix, wage increases, and technology in determining hospital costs. As a measure for technology, Davis included a time trend variable to capture the residual effect of increases in average costs over time. Her results indicated that the 38% of hospital costs that is not explained by demand and supply variables, is taken to be the effect of technology. However she was aware that the time trend could have included also basic shifts in patient, physician or hospital behavior, therefore it can be argued that this study puts an upper limit on the effect of technology.

Feldstein's econometric work (1977) looked at technology as a factor contributing to soaring costs in hospitals. Nevertheless in his framework technology is merely a passive factor, since the central role is given to rising health insurance coverage: insurance enables hospital management to alter the mix of services provided and the new medical services introduced are more expensive as they incorporate new technology. Feldstein ran his empirical work on aggregated data from US hospitals and health insurers, without taking into account of the purpose, or nature, of the diverse medical services.

More recently Blank and Vogelaar (2004) studied the effect of technical change in Dutch hospital industry. They estimated a cost function on data in the period 1993-2000, using as a proxy for technical change a technology index which is a weighted sum of time dummies. They ended that technical change is embodied (input-biased), not scale augmenting (no differences between small and large hospitals) and shock wise.

Farsi and Filippini (2006) analyzed a panel data of Swiss general hospitals over the four-year period between 1998 and 2001. They used a sub-sample of 156 hospitals to estimate a total cost function for an econometric analysis of efficiency. The year dummies were deemed to represent technological change and the estimated coefficients indicated that total hospital costs have grown about 4 percent by year. The authors recognize also that these dummies might capture not only technological progress in medical care, but also other year-specific effects such as changes in quality of reporting DRG cases.

Finally Blank and Van Hulst (2009) studied the relationship between technology and productivity in Dutch hospitals between 1995 and 2002. Their main contribution was to explicitly inventory innovations, which were aggregated into a limited number of homogeneous innovation clusters, measured by technology index numbers. Their estimates indicate that some technology clusters increase total costs, while other ones reduce them.

1.3 Hospital technology

In theoretical and empirical works, hospital technology is characterized in a variety of ways, and measured with a broad set of instruments. Some studies do not even define the concept clearly, even though an unambiguous and precise quantification is needed to answering both theoretical and policy issues. Spetz and Maiuro (2004) explore the meaning of the term hospital technology and provide an excellent review of the measures of this concept. Broadly speaking, with the term hospital technology we refer to procedures, devices, and processes by which hospital care is delivered. Examples of technological progress would include new medical and surgical procedures such as cardiac catheterization or open-heart surgery, drugs (e.g., statins), medical equipment like magnetic resonance imaging (MRI), and new support systems (e.g., electronic medical records and telemedicine).

We have seen that in a cost function or efficiency measurement setting, adding simply a time trend variable or a set of time dummies to the equation to be estimated might not be entirely satisfactory since this brings about only a shift of the frontier. Therefore, following the Blank and Van Hulst (2009) research, we approximate innovations with an index of available technologies. In order to be useful for our analysis, this index should be comparable across hospitals and over time. Baker and Spetz (2000) introduced an aggregation function of technologies, which is known as Saidin index

$$N_{ht} = \sum_{p}^{P} \omega_{pt} n_{hpt} \tag{1.1}$$

where n_{hpt} can be either 1 or 0 depending on whether technology p is available or not at time t for hospital h. The weight ω_{pt} reflects the percentage of H hospitals that do not possess the technology or service in a given year, i.e.

$$\omega_{pt} = 1 - \frac{1}{H}\sum_{h=1}^{H} n_{pht} \tag{1.2}$$

Innovations that were rather uncommon because they are new, expensive, or difficult to implement get higher weights in this measure. Technologies that are ordinary receive lower weights. This weighting scheme corresponds with most peoples idea of what defines high technology: something which is rare due to newness, expense, or difficulty of operation. When a technology becomes common, it is no longer perceived as being of a high level.

Two problems arise when using the Saidin index: 1) the set of technologies under consideration changes each year as new innovations are introduced to medicine and to surveys. Hence discontinuities can be introduced into the time series of index values; 2) changing the weights each year may not identify changes in technology over time.[3]

We cope with the first problem by keeping fixed and consistent over time the list of services needed to produce the index (see Table 1.1). On the other hand a solution to the second concern is less straightforward. As opposed to Blank and Van Hulst (2009) we rejected the hypothesis of keeping fixed the weights, since this may produce a poor indicator of the current state of the world, especially in the case of a long panel. US has a dynamic health industry so that innovations change in importance over short periods of time. It is likely that the assumption of technologies having fixed values over twelve years, the length of our panel, is flawed. Our idea was to apply to our technology index a technique known as chain-linking, which is currently used in National Accounts to provide chained volume measures for several series including GDP, household final consumption expenditures, gross fixed capital formation and the like. With annual chain-linking we calculate the value of the index, summing up technologies on the basis of current weights and previous years weights:

$$N_t = \begin{cases} \sum_p^P \omega_{pt} n_{pt} & \text{if } t = T \\ \sum_p^P \omega_{pt} n_{pt} \cdot \frac{\sum_p^P \omega_{pT} n_{p,t+1}}{\sum_p^P \omega_{pt} n_{p,t+1}} & \text{otherwise} \end{cases} \tag{1.3}$$

With this method we aggregate technologies on a more frequent basis. It can be thought of as rebasing every year. Instead of referring back to weights from the most recent base year, the technology index for each year is produced in weights of the previous year. These measures are

[3] Hospitals rarely shut down services, their relative rarity indicated by the weights could be expected to fall through time as more hospitals adopt new technologies. The index values would thus tend to fall even for hospitals that did not change their service set each year.

then "chain-linked" together to produce a continuous time series.

In figure 1.1 we reported the pattern of the average index of technology using three different base years and our new chain-linked measure. Our sample of hospitals between 1996 and 2007 confirms the widespread impression in the literature concerning the steady increase of technological progress, with the latest years characterized by a more rapid growth. Not surprisingly the index calculated with 1997 taken as base year shows the highest value throughout the period. This is due to the fact that bigger weights are obtained when fewer hospitals hold a given technology, something which makes more sense when going back in the past. Further the chain-linked measure is reasonably very similar to the 2007 based index at the end of the time span and slightly diverging at the beginning.[4]

1.4 Economic model

Assessing one hospital's costs behavior requires the adoption of an explicit assumption concerning the state of equilibrium among observations in the sample. In this paper we assume a neo-classical cost function in which hospitals minimize costs, given that input prices and outputs are exogenous. Exogeneity of input prices is derived from the hypothesis that factor markets are competitive and free from monopsonistic pressures. While output levels are determined by the demand of patients. The underlying assumption is that doctors are perfect agents with full information about their patients' utility function and that their own preferences are not affecting the evolution of the treatment. Further, hospitals do not rapidly adjust all factors of production in response to variations in output quantities or input prices. In such framework hospitals will employ optimal levels of the easily adjustable inputs, given the existing non-optimal levels of the fixed inputs. The variable cost function is specified as

$$VC = VC(\mathbf{Y}, \mathbf{W}, \mathbf{K}, N) \tag{1.4}$$

where VC equals variable costs, $\mathbf{Y}$ is a vector of outputs, $\mathbf{W}$ is a vector of input prices, $\mathbf{K}$ is a vector of fixed inputs and N is technology.

The cost-minimization assumption can been questioned, given the not-for-profit status of most structures. Still, Pauly (1987) shows that cost minimization is coherent with many non-profit theories of behavior, especially when entry is free. Further, the DRG prospective payment system and tight reimbursement policies from third party insurers force hospital management to adopt cost-saving policies.

In this paper we suggest an explicit modelling of the influence of technical development. The choice of adopting or not a new technology is the result of several factors, one of them being the effect on productivity. However technology is not strictly endogenous, since once innovations have been set up, they are exogenous in the subsequent years. Therefore, we abstract from this issue

[4]Note that by construction the 2007 based index and the chain-linked index must be equal in 2007.

and assume the exogeneity of technology.

In order to estimate equation 1.4, we adopt the generalized translog multiproduct cost function discussed by Caves et al. (1980). With this specification we apply the Box-Cox transformation to those output variables having zero values. The ordinary translog function in fact is not suitable, since the natural logarithm of zero is undefined.[5] In addition to the variables indicated in equation 1.4 we also included a bunch of controls which are described in the data section. The hybrid generalized translog function to be estimated is thus written as

$$\begin{aligned}
\ln VC_t &= \alpha_0 + \sum_{i=1}^{I} \alpha_i \left(\frac{Y_{it}^{\lambda} - 1}{\lambda} \right) + \sum_{j=1}^{J} \beta_j \ln w_{jt} + \gamma_k \ln K_t + \delta_n \ln N_t \\
&+ \frac{1}{2} \sum_{i=1}^{I} \sum_{i'=1}^{I} \alpha_{ii'} \left(\frac{Y_{it}^{\lambda} - 1}{\lambda} \right) \left(\frac{Y_{i't}^{\lambda} - 1}{\lambda} \right) + \frac{1}{2} \sum_{j=1}^{J} \sum_{j'=1}^{J} \beta_{jj'} \ln w_{jt} \ln w_{j't} \\
&+ \frac{1}{2} \gamma_{kk} \left(\ln K_t \right)^2 + \frac{1}{2} \delta_{nn} \left(\ln N_t \right)^2 + \frac{1}{2} \sum_{i=1}^{I} \sum_{j=1}^{J} \zeta_{ij} \left(\frac{Y_{it}^{\lambda} - 1}{\lambda} \right) \ln w_{jt} \\
&+ \sum_{i}^{I} \eta_i \left(\frac{Y_{it}^{\lambda} - 1}{\lambda} \right) \ln K_t + \sum_{i}^{I} \vartheta_i \left(\frac{Y_{it}^{\lambda} - 1}{\lambda} \right) \ln N_t \\
&+ \sum_{j}^{J} \mu_j \ln w_{jt} \ln K_t + \sum_{j}^{J} \nu_j \ln w_{jt} \ln N_t + \xi \ln K_t \ln N_t + \sum_{l}^{L} \pi_l z_{lt} + \sum_{t}^{T} \psi_t A_t + \epsilon_t \qquad (1.5)
\end{aligned}$$

where Y_{it} is the i-th output at time t,[6] w_{jt} is the j-th input price, K_t is the fixed capital input stock, N_t is the technology index, z_{lt} is the l-th control variable and A_t represents time dummies. We imposed a symmetry constraint on the $\beta_{jj'}$ and the ζ_{ij}, i.e. $\beta_{jj'} = \beta_{j'j}$. Further we need more constraints on the parameter values in order to impose linear homogeneity in factor prices

$$\begin{aligned}
&\sum_{j} \beta_j = 1 \\
&\sum_{j} \zeta_{ij} = \sum_{j} \beta_{jj'} = \sum_{j} \mu_j = \sum_{j} \nu_j = 0
\end{aligned}$$

[5]The only alternative to the Box-Cox transformation involves substituting arbitrarily small positive numbers for the zero values, i.e we transform x in $\ln(x+\epsilon)$. Usually results coming from this approach are sensitive to the value chosen. In our study we did some sensitivity checks, by varying the value of ϵ. Results did not change significantly.

[6]Obviously $\frac{Y_{it}^{\lambda}-1}{\lambda}$ is the Box-cox transformed output.

Following Shepard's lemma we derive a set of cost share equations from the cost function

$$\begin{aligned} S_i &= \frac{\partial VC_t}{\partial \ln w_{jt}} \\ &= \beta_j + \sum_{j'} \beta_{jj'} \ln w_{jt} + \sum_i \zeta_{ij} \left(\frac{Y_{it}^{\lambda} - 1}{\lambda} \right) + \mu_j \ln K_t + \nu_j \ln N_t \end{aligned} \tag{1.6}$$

Since cost-shares sum up to unity, we delete one equation from the system and estimate the remaining ones jointly with the cost function by Zellner's iterative seemingly unrelated regressions. In order to grab the effect of technology on costs, we evaluate the derivative of the logarithm of variable costs with respect to the technology index

$$\frac{\partial \ln VC_t}{\partial \ln N_t} = \delta_n + \delta_{nn} \frac{\ln N_t}{N_t} + \sum_i \vartheta_i \left(\frac{Y_{it}^{\lambda} - 1}{\lambda} \right) + \sum_j \nu_j \ln w_{jt} + \xi \ln K_t \tag{1.7}$$

As a form of comparison, we estimate an alternative specification of equation 1.4 which takes into account explicitly technology without relying on any synthetic measure of innovations. Specifically we change the generalized translog equation 1.5 by both eliminating the parameters δ_n, δ_{nn}, ϑ_i, ν_j and adding a set of dummies representing all technologies available at a given point in time. This technology dummy variables (TDV) approach is expressed as follows

$$\begin{aligned} \ln VC_t &= \alpha_0 + \sum_{i=1}^{I} \alpha_i \left(\frac{Y_{it}^{\lambda} - 1}{\lambda} \right) + \sum_{j=1}^{J} \beta_j \ln w_{jt} + \gamma_k \ln K_t && (1.8) \\ &+ \frac{1}{2} \sum_{i=1}^{I} \sum_{i'=1}^{I} \alpha_{ii'} \left(\frac{Y_{it}^{\lambda} - 1}{\lambda} \right) \left(\frac{Y_{i't}^{\lambda} - 1}{\lambda} \right) + \frac{1}{2} \sum_{j=1}^{J} \sum_{j'=1}^{J} \beta_{jj'} \ln w_{jt} \ln w_{j't} \\ &+ \frac{1}{2} \gamma_{kk} \left(\ln K_t \right)^2 + \frac{1}{2} \sum_{i=1}^{I} \sum_{j=1}^{J} \zeta_{ij} \left(\frac{Y_{it}^{\lambda} - 1}{\lambda} \right) \ln w_{jt} + \sum_{i}^{I} \eta_i \left(\frac{Y_{it}^{\lambda} - 1}{\lambda} \right) \ln K_t \\ &+ \sum_{j}^{J} \mu_j \ln w_{jt} \ln K_t + \xi \ln K_t \ln N_t + \sum_{l}^{L} \pi_l z_{lt} + \sum_{t}^{T} \psi_t A_t + \sum_{p=1}^{P} \rho_p n_{pt} + \epsilon_t && (1.9) \end{aligned}$$

where n_{pt} represent the availability of technology p at time t and $\rho_p = \frac{\partial \ln VC}{\partial n_p}$ is the coefficient giving the partial effect of technology p on the cost frontier. Following Kennedy (1981) the total percentage effect of technology dummies on variable costs is given by the exponentiated sum of the ρ coefficients corrected by their respective variances, i.e. $\sum_{p=1}^{P} \left(\exp \left[\hat{\rho}_p - \frac{\hat{Var}(\hat{\rho}_p)}{2} \right] - 1 \right)$. However for small values of each $\hat{\rho}_p$ this formula is substantially equal to[7]

[7] As rule of thumb, a coefficient smaller than 0.1 can be deemed a "reasonable" threshold value.

$$\sum_{p=1}^{P} \frac{\partial \ln VC}{\partial n_p} = \sum_{p=1}^{P} \hat{\rho}_p \tag{1.10}$$

1.5 Data

Sources, eligibility and sample selection

American Hospital Association (AHA) survey and Medicare cost reports represent the main sources of information for this study. From the former we got data on outputs, technology adoption and some other hospital characteristics. While the latter provided us all financial data. Other sources like the Current Population Survey (CPS), the Centers for Medicare and Medicaid Services (CMS) and the National Center for Education Statistics were employed in order to control for environmental factors such as insurance, market structure and demographic characteristics.

We limited our analysis to short-term hospitals, since long-term and rehabilitation structures generally serve a very different production function. We deemed hospitals eligible when they had consistent Health Care Financing Administration (HCFA) identifiers, which made possible the matching between the AHA survey files and Medicare reports. Then we had to pull out observations with inconsistent Federal Information Processing Standard (FIPS) county code, which we used to merge hospitals with environmental variables. Observations with missing input prices and outputs were also discarded. Then we deleted observations with inconsistent cost data and outliers.[8] Our last step was to select observations always available throughout the period 1996-2007. We ended up with a perfectly balanced panel of 2230 hospitals, for a total 26760 observations. All detailed steps of hospitals eligibility and selection criterion are summed up in table 3.4.

The choice of undertaking the analysis over the hospitals that we can keep track all over the twelve years is based on the fact that during this time span many hospitals opened, other ones closed their operations with/without reopening or faced a merge/acquisition process. It is not possible with the data at our hand to know what is the event that caused a stop in the series. The treatment of the merged hospitals would be highly problematic. We may theoretically merge their financial and stock data for the years they were separated, but it is not clear whether the behavior of the resulting hospital would respond to the same scheme of incentives previous to the merge/acquisition event. Similarly handling hospital openings is equally important because new hospitals tend to face severe start-up costs. Further, a closure is an event that is a likely consequence of a bad financial situation, which have to be differently analyzed with respect to hospitals that are going to acquire other structures. Both openings and closure are events that shift the cost frontier.

[8] We consider an observation outlier if at least one of its input prices is smaller than the first percentile or greater than the ninety-ninth percentile of the respective input price or total discharges are smaller than the first percentile of total discharges.

Being impossible to distinguish among hospitals with simple problems of data misreporting and hospitals experiencing one of the above mentioned events, we decided to restrict the analysis to hospitals with a complete and "safe" information set.

Short-run cost function parameters

In any multiproduct hospital cost function, identifying the outputs always involves a tradeoff between the wish to grasp all aspects of a hospital activity and the need to limit its range in order to make estimation feasible. In this study the latter side of the tradeoff does not represent a serious concern, given the availability of a large sample. In our model we use three distinct types of outputs as the basis for estimation: hospital unit inpatient discharges, nursing home discharges and outpatient visits. We further disaggregate the hospital unit inpatient discharges into Medicare and non-Medicare, because of the policy relevance in the question of how Medicare outputs affect hospital costs. We preferred inpatient discharges to inpatient days because in a prospective payment system the latter variable may reflect more a productive choice of the hospital management rather than patients' demand.[9]

Input prices are measured in terms of expenses incurred by each hospital, deflated at 2007 prices. In this study average annual salary per full-time equivalent employee is used as price of labor. Unfortunately from the Medicare reports we are not able to get a more refined measure of labor prices which recognizes different skill requirements. From total costs we subtract the costs of labor and costs of capital and get a residual measure of costs of material and supplies. We divide this amount by total admissions and the result is our admittedly unattractive measure of price of materials and supplies. Further, the number of beds is the measure for fixed capital stock, a solution generally taken in the literature.

As it can be seen from table 1.3, the cost per admission steadily increased in the period considered from about 2200$ in 1996 up to 3200$ in 2007. Similarly hospital unit discharges and outpatient visits rose and reached their peaks in 2007, while nursing home services had a severe contraction from the top of 1998. Input prices also increased: our measure of materials and supplies price has grown from 1220$ per admission in 1997 to almost 1900$ in 2007. While annual wage per full time equivalent worker on average rose from 51530$ up to 55140$ in 2007. Further the fixed capital stock is the variable showing more stability: the number of beds has been declining since 1996 until 2001 and then it had a constant light increase without never reaching the peaks of the beginning of the period.

[9] In the DRG system there are strong incentives for the hospital management to adopt opportunistic behavior as described by Ellis and McGuire [**?**]. Case-mix selection, cream skimming, skimping or upcoding are events more likely to affect the length of stay rather than the level of discharges.

Explanatory variables

Given the heterogeneity inherent in the categories of output volume, we included a set of variables elaborating on the clinical composition of each output. Variations in output characteristics are measured by the percentage of beds in intensive care units, the ratio of births to admissions, the number of inpatient surgical operations per admission and the share of Medicaid and Medicare discharges. As additional hospital controls we considered the type of ownership, in the form of a dummy variable whether the hospital is private for profit and private not-for-profit (the base category is given therefore by structures run by the government). We included other dummy variables for teaching hospitals, hospitals operating subsidiaries, contract-managed and participating in a network, and hospitals having a formal written contract with a Health Maintenance Organization (HMO) or a Preferred Provider Organization (PPO). Further we measured competitive pressures in the hospital's market by a Hirschman-Herfindahl index, a standard economic measure of industry concentration that is used to reflect the distribution of admissions in hospitals in the market area. Moreover we have added several more explanatory variable concerning the insurance environment, demographic factors and schooling levels in the area, which are described in table 1.4.

Finally in order to capture unmeasured technological change and variation in unobserved variables such as quality we have included a set of year dummies, where the base year is represented by 1996.

1.6 Results

In table 1.5 we report results obtained by estimating equation 1.5, using different sets of explanatory variables. In column 1 we have just added time dummies to technology parameters, while starting from column 2 to column 5 we subsequently insert hospital characteristics, insurance environment variables, demographic characteristics and state dummies. Our first measure of interest is given by the elasticity of variable costs with respect to technology index, which is always positive and statistically significant.[10] The magnitude of this elasticity goes down as the number of controls increase in the estimation. In column 5, which represents the model where most sources of variation are controlled for, the value is 0.067. The interpretation of this elasticity is not straightforward, but still possible. At means, a 10% increase in the value of the index corresponds to almost a 0.7% increase in variable costs. Since on average our chain-linked measure of technology for all the years is 6.55, when we increase it by 0.655 (10% of 6.55) this equals the added contribution of an innovation hold by roughly 35% of the sample of hospitals. Therefore adding a relatively new technology has an increasing effect on costs of almost 18$ per admission (0.67% of 2680$, see table 1.3), or alternatively 800,000$ overall. Own-price elasticities of inputs are correctly negative and

[10]Standard errors for all elasticities were computed by applying the delta method to linearize the elasticity functions around the estimated parameter values and then using standard formulas for the variances and covariances of linear functions of random variables.

largely significant and their magnitude increases as the number of controls increase too. While the elasticity of cost with respect to capital measured by beds is positive as one may expect. What is surprising in these estimates is the magnitude of the year dummies. Not only there is an increasing positive trend but also the level is higher when we add more shifting factors to the frontier. This might be interpreted as year dummies are capturing unmeasured technical change, even though we have explicitly specified innovations into the model.

Marginal cost of output i is calculated by multiplying the elasticity of cost with respect to the given output i times the ratio of average costs and average output

$$
\begin{aligned}
MC_{Y_i} &= \frac{\partial VC_i}{\partial Y_i} = E_{CY_i} \frac{\overline{VC}_i}{\overline{Y}_i} \\
&= \left[\alpha_i + \sum_{i'=1}^{I} \alpha_{ii'} \frac{Y_{i'}^{\lambda} - 1}{\lambda} + \sum_j \zeta_{ij} \ln w_j + \eta_i \ln K + \vartheta_i \ln N \right] Y_i^{\lambda} \frac{\overline{VC}_i}{\overline{Y}_i} \qquad (1.11)
\end{aligned}
$$

As it can be seen from table 1.6, computed marginal costs are correctly positive for all outputs. We did not find any recent studies to which relate these figures. Dor and Farley (1996) estimates refer to a limited sample of 331 short-term facilities in the period 1985-1987. They got a marginal cost of inpatient medicare discharge higher than that of other types of inpatient discharges. Other works in the 80's report approximately a marginal cost of 8000$ in 1994 value for inpatient discharges.[11] Vita (1990) estimates an outpatient visit marginal cost of 73$ for a cross-section of hospitals in 1983. Taking these numbers with extreme caution as a form of comparison, it seems that our figures can be deemed reasonable.

In order to validate our estimates presented in table 1.5, we show in table 1.7 the outcome of our TDV equation. It can be seen that results are very similar to the technology index approach. Time dummies have the same increasing pattern, while own-price elasticities and capital elasticity are of the same size. Now the measure of technology effect differs, since it represents two extreme cases: hospitals holding all technologies vs. hospitals without any innovations. When we control for all available sources of heterogeneity, this sort of "switch-on" effect of hospitals holding all technologies is reflected in a 23% increase in the level of variable costs. Obviously any intermediate situation has to be analyzed by looking at technology specific coefficients. The TDV approach in fact helps us discerning which are the innovations that positively or negatively contribute to the cost frontier. Among the thirty-three given technologies, twenty-five bring about an upward shift of the cost function, nineteen of them being statistically significant (results not shown). Also in this case adding more controlling factors in the estimation substantially decreases the measured technological effect and increases the unmeasured one represented by the time dummies. This

[11] See for instance Robinson and Luft (1985) and Granneman et al. (1986).

result might be due to the limitation of using technology dummies both in the computation of the technology index and also in a more direct way into the estimating system of equations. In fact what we measure is simply the availability or not of certain technologies. If we think to a specific innovation, say for instance a MRI, we know that MRI equipment is very different in terms of both expensiveness and operational contents. Therefore we cannot distinguish among latest fashion MRI and those making the most simple imaging. This obviously may come at a cost of underestimating the impact of MRI on variable costs, which is absorbed into the time trend.

Furthermore it is of interest analyzing the pattern of the effects of technologies through time. We might expect that some new technologies strongly increase costs once they are set up, but after some years the sign of the effect is reversed. Other innovations might increase costs at an increasing or decreasing rate. Therefore we put more structure in the model by adding interactions of time dummies with technology dummies. This means we are adding 396 interactions into model expressed by equation 1.9 (33 dummies of technology times 12 year dummies). Because of the interactions, in order to avoid perfect collinearity we have either to drop technology dummies or year dummies. We have opted for the former choice, since we are still interested in checking the pattern of time dummies and because in this way it is possible to get a direct estimate of the specific technology effect also in the first year of the survey. It is not possible for space reasons to show all interactions terms. However in table 1.8 we summarize results of this "giant" regression. Under the column with the plus sign we show technologies reporting a majority of positive signs, i.e. those bringing about an upward shift of the frontier. While technologies under the minus sign cause a decrease in the frontier. The "Increasing trend" row and "Decreasing trend" row correspond trivially to technologies showing a coefficient value which is increasingly or decreasingly greater in absolute terms through time. The "Constant" row refers to technologies without a clear pattern, while "Mixed evidence" points out technologies whose effects completely change sign after some years. Finally in parentheses we inserted the number of coefficients with prevailing sign, followed by the number of those which are statistically significant. For instance for the variable `tplnthos`, we estimated twelve positive coefficients, eleven of them being statistically significant. Reasonably there is a lot of heterogeneity in our estimates and most innovations do not present a clear trend. Transplant services and ultrasound devices are the technologies showing the less ambiguous results, both in terms of significance and magnitude of the coefficients. Transplant services strongly contribute to an upward shift of the frontier that is increasing through time. While the reverse is given for ultrasound equipment. Consistently with literature, MRI equipment adoption is increasingly contributing to the rise of hospital costs (see Baker, 2001), even though only a third of the coefficients are significant. The estimate of the sum of impacts of all technologies jointly considered is about 0.251, which is very similar to the case without interactions. In figure 1.2 we report the pattern of the measured technological effect. We called it as cumulative technological effect since each point in the graph is the result of the sum, up to year t_i, of the sum of derivatives of the interactions with respect to technology dummy variables evaluated at the mean of time dummies, i.e.

$$Cumul_{t_i} = \sum_{t=1}^{t_i} \sum_{p=1}^{P} \frac{\partial \ln VC}{\partial n_{pt}} \overline{A}_t$$

The slope of this line is slightly steeper in the first years of the survey, and always between 0.017 and 0.025, looking very similar to a linear trend. Further, the estimated coefficients of time dummies, which we do not report, are now not significant and overall they do not show any specific pattern. This was somehow expected since the time dummies have been interacted with all technologies.

1.7 Conclusions

In this paper we assess quantitatively the impact of technology on hospital costs, which makes up the major share of total US health spending. With the term hospital technology we refer to procedures, devices, and processes by which hospital care is delivered. We avert the common practice applied in production economics to use time trends or dummies, by approximating innovations with a novel index of available technologies, which guarantees comparability across hospitals and over time. AHA surveys provide us information on the availability of a host of technologies, while for financial data we use Medicare cost reports.

Our results are consistent with the view that technology is correlated with a rise in hospital care spending. Elasticity estimates point out that adding a relatively new technology has an increasing effect on costs of almost 18$ per admission, i.e. 800,000$ overall. Further there is a substantial increasing positive trend, which is more robust as much as we add controlling factors to the model. This unmeasured technological progress is confirmed by a simple technology dummies approach, which has been implemented to validate the first set of estimates. The reason for the time trend being still not irrelevant is due to the definition of technology availability, which in some cases is still too general to capture differences between high vs. low tech innovations. Finally we point out that while the net effect of technology is positive, innovations can be either cost-saving or cost-pushing or not having even any significant influence on costs. The pattern of these effects through time cannot be generalized and is very diverse among the innovations collected in this study.

1.8 References

Baker, L. (2001) "Managed care and technology adoption in health care: evidence from magnetic resonance imaging", *J.Health Econ.*, **20**: 395-421.

Baker, L. and J. Spetz (2000) "Managed care and medical technology growth" in A. Garber (Ed.), *Frontiers in Health Policy Research*, Vol. 2, Cambridge, MA: MIT Press.

Blank, J.L.T and B.L. Van Hulst (2009) "Productive iinovations in hospitals: an empirical research on the relation between technology and productivity in the Dutch hospital industry", *Health Econ.*, **18**: 665-679.

Blank, J.L.T and I. Vogelaar (2004) "Specifying technical change: a research on the nature of technical change in Dutch hospital industry", *Quart. Rev. Econ. Finance*, **44**: 448-463.

Caves, D.W., L.R. Christensen and M.W. Tretheway (1980) "Flexible cost functions for multiproduct firms", *Rev. Econ. Statist.*, **62:3**: 477-481.

Davis, K. (1974) "The role of technology, demand and labour markets in the determination of hospital cost" in M. Perlman (Ed.), *The Economics of Health and Medical Care*, London: Macmillan, 283-301.

Dor, A. and D.E. Farley (1996) "Payment source and the cost of hospital care: Evidence from a multiproduct cost function with multiple players", *J.Health Econ.*, **15**: 1-21.

Ellis, R.P. and T.G. McGuire (1996) "Hospital response to prospective payment: Moral hazard, selection, and practice-style effects", *J.Health Econ.*, **15**: 257-277.

Farsi, M. and M. Filippini (2006) "An analysis of efficiency and productivity in Swiss hospitals", *Swiss Journ. Econ. Stat.*, **142(1)**: 1-37.

Feldstein, M.S. (1977) "Quality change and the demand for hospital care", *Econometrica*, **45**: 1681-1702.

Granneman, T., R. Brown and M. Pauly (1986) "Estimating hospital costs: a multiple output analysis", *J.Health Econ.*, **5(2)**: 107-127.

Kennedy, P.E. (1981) "Estimation with correctly interpreted dummy variables in semilogarithmic equations", *Amer. Econ. Rev.*, **71(4)**: 801.

J.P. Newhouse (1992) "Medical care costs: how much welfare loss?", *J.Econ. Perspect.*, **6(3)**: 3-21.

Okunade, A.A. and V.N.R. Murthy (2002) "Technology as a major driver of health care costs: a cointegration analysis of the Newhouse conjecture", *J.Health Econ.*, **21**: 147-159.

Pauly, M.V. (1987) "Nonprofit firms in medical markets", *Amer. Econ. Rev.*, **77(2)**: 257-262

Robinson, J. and H.Luft (1985) "The impact of hospital structure on patient volume, average length of stay, and the cost of care", *J.Health Econ.*, **4(4)**: 333-356.

Spetz, J. and L.S. Maiuro (2004) "Measuring levels of technology in hospitals", *Quart. Rev. Econ. Finance*, **44**: 430-447.

Vita, M.G. (1990) "Exlporing hospital production relationships with flexible functional forms", *J.Health Econ.*, **9**: 1-21.

1.9 Tables

Table 1.1: List of technologies

Variable name	Description
aidsshos	HIV-AIDS services
airbhos	Airborne infection isolation room
brnhos	Burn care
bwhthos	Bariatric/weight control services
caoshos	Computer assisted orthopedic surgery
cardhos	Cardiac surgery
cclabhos	Cardiac catheterization
chthhos	Chemoterapy
cichos	Cardiac intensive care
ctscnhos	Computed-tomography scanner (CT)
dradfhos	Diagnostic radioisotope facility
ebcthos	Electron Beam Computed Tomography (EBCT)
eswlhos	Extracorporeal shock-wave lithotripter (ESWL)
ffdmhos	Full-field digital mammography
hemohos	Hemodialysis services
mammshos	Breast cancer screening/mammograms
mrihos	Magnetic resonance imaging (MRI)
msctghos	Multislice spiral computed tomography 64 + slice
mscthos	Multislice spiral computed tomography <64 slice
msichos	Medical/surgical intensive care
nichos	Neonatal intensive care
oncolhos	Oncology services
ortohos	Orthopedic services
pedichos	Pediatric intensive care
petcthos	Positron emission tomography/CT (PET/CT)
pethos	Positron emission tomography (PET)
radthhos	Radiology therapeutic
robohos	Robotic surgery
specthos	Single photon emission computed tomography (SPECT)
tplnthos	Transplant services
traumhos	Certified trauma center
ultsnhos	Ultrasound
vrcshos	Virtual colonoscopy

Table 1.2: Eligibility and selection criterion

Step	**# obs**	**# Dropouts**	
Starting observations	65,194		-
Inconsistent Medicare ID		4,101	
	61,093		-
Inconsistent FIPS county code		561	
	60,532		-
Missing input price		6,303	
	54,229		-
Missing outputs		3	
	54,226		-
Inconsistent cost data		23	
	54,203		-
Outliers		3,678	
Total eligible	50,525		
Selection		23,765	
Total	26,760	38,634	

Table 1.3: **Descriptive statistics**

Year	**CPI**	**Y1**	**Y2**	**Y3**	**Y4**	**wL**	**wS**	**Beds**
1996	2211	2722	4225	91	97901	51534	1220	174
	(1026)	(2493)	(4823)	(212)	(108242)	(13282)	(619)	(143)
1997	2277	2807	4308	117	100614	51560	1262	171
	(1012)	(2571)	(4981)	(349)	(115350)	(10515)	(609)	(142)
1998	2370	2829	4389	120	106748	52515	1315	169
	(1061)	(2591)	(5044)	(458)	(122877)	(10511)	(625)	(143)
1999	2448	2880	4511	120	113940	53179	1366	166
	(1116)	(2651)	(5276)	(250)	(132710)	(10798)	(660)	(143)
2000	2562	3169	4502	105	121064	54085	1440	159
	(1216)	(3042)	(5280)	(231)	(139294)	(11257)	(713)	(141)
2001	2635	3274	4621	95	125123	54678	1489	159
	(1223)	(3120)	(5376)	(222)	(144492)	(10641)	(719)	(142)
2002	2719	3326	4713	95	129426	54989	1550	160
	(1268)	(3192)	(5439)	(214)	(151963)	(11004)	(757)	(144)
2003	2823	3365	4802	87	131673	54793	1628	160
	(1371)	(3224)	(5584)	(224)	(154830)	(10564)	(825)	(144)
2004	2890	3452	4829	73	135203	54829	1673	161
	(1473)	(3326)	(5584)	(199)	(166429)	(11658)	(881)	(146)
2005	2951	3525	4814	74	137212	54826	1714	162
	(1441)	(3375)	(5571)	(208)	(168728)	(11102)	(868)	(148)
2006	3073	3491	4849	72	140281	54647	1791	162
	(1584)	(3401)	(5684)	(199)	(177718)	(10888)	(952)	(149)
2007	3202	3538	4854	66	142935	55141	1866	164
	(1699)	(3510)	(5793)	(191)	(184361)	(11401)	(1019)	(153)
Total	2680	3198	4618	93	123510	53898	1526	164
	(1343)	(3075)	(5380)	(258)	(149821)	(11231)	(808)	(145)

Notes: Standard deviations in parentheses. CPI=Cost per inpatient admission, Y1=inpatient Medicare discharges, Y2=inpatient other discharges, Y3=nursing home discharges, Y4=outpatient visits, wL=price of labor, wS=price of supplies

Table 1.4: Control variables summary statistics

Variable	Aggregation	Mean	SD
Output composition			
Beds in intensive care units	Hospital	7.54 %	0.09
Ratio of births to total admissions	Hospital	10.80 %	0.08
Inp. surg operation per admission	Hospital	0.26	0.18
Inp. Medicare discharges	Hospital	42.73 %	0.15
Inp. Medicaid discharges	Hospital	14.85 %	0.11
Hospital characteristics			
Private not-for-profit	Hospital	62.91 %	0.48
Private for-profit	Hospital	17.49 %	0.38
Teaching	Hospital	17.99 %	0.38
Subsidiaries	Hospital	21.23 %	0.41
Contract-managed	Hospital	10.62 %	0.31
Network	Hospital	33.68 %	0.47
Herfindhal index	Hospital	40.67 %	0.41
Insurance environment			
Managed Care penetration	County	6.59 %	0.11
Hospital has written contract with HMO	County	58.57 %	0.33
Hospital has written contract with PPO	County	73.94 %	0.24
Uninsured	State	13.77 %	3.93
Priv. insur. - employment based	State	62.31 %	5.84
Priv. insur. - directly purchased	State	10.30 %	3.19
Pub. insur. - Medicaid	State	11.51 %	3.61
Pub. insur. - Medicare	State	13.81 %	2.29
Demographic factors			
Log household median income, 2007 US$	County	10.67 %	0.23
Poverty rate	County	13.73 %	5.44
Poverty rate - age 0-17	County	19.07 %	7.77
Population - age 0-14	County	20.47 %	0.03
Population - age 15-64	County	65.51 %	0.03
Population - age 65+	County	14.02 %	0.04
Female population	County	50.75 %	0.02
Female population - age 15-64	County	20.62 %	0.02

Table 1.5: Estimation results with index of technology

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Year 1997	.007	.008	.011 *	.007	.008
	(.006)	(.005)	(.005)	(.005)	(.005)
Year 1998	.01 †	.011 *	.012 *	.006	.014 *
	(.006)	(.005)	(.005)	(.005)	(.005)
Year 1999	.01 †	.013 *	.007	.002	.017 **
	(.006)	(.005)	(.005)	(.005)	(.006)
Year 2000	.021 **	.032 **	.021 **	.014 *	.035 **
	(.006)	(.005)	(.005)	(.006)	(.006)
Year 2001	.022 **	.034 **	.02 **	.017 **	.037 **
	(.006)	(.005)	(.006)	(.006)	(.006)
Year 2002	.028 **	.039 **	.028 **	.025 **	.042 **
	(.006)	(.005)	(.006)	(.006)	(.006)
Year 2003	.044 **	.055 **	.043 **	.035 **	.052 **
	(.006)	(.005)	(.006)	(.006)	(.006)
Year 2004	.052 **	.065 **	.051 **	.046 **	.064 **
	(.006)	(.005)	(.006)	(.006)	(.006)
Year 2005	.057 **	.074 **	.06 **	.056 **	.075 **
	(.006)	(.005)	(.006)	(.006)	(.007)
Year 2006	.062 **	.076 **	.065 **	.063 **	.081 **
	(.006)	(.006)	(.006)	(.006)	(.007)
Year 2007	.066 **	.086 **	.071 **	.07 **	.093 **
	(.006)	(.006)	(.006)	(.007)	(.007)
$\partial \ln VC / \partial \ln N$	.114 **	.091 **	.091 **	.085 **	.067 **
	(.003)	(.003)	(.003)	(.003)	(.003)
$\partial \ln VC / \partial \ln K$	.354 **	.352 **	.345 **	.335 **	.336 **
	(.006)	(.006)	(.006)	(.006)	(.006)
Own-price: labor	-.147 **	-.178 **	-.191 **	-.198 **	-.211 **
	(.013)	(.012)	(.012)	(.012)	(.012)
Own-price: supplies	-.114 **	-.139 **	-.149 **	-.154 **	-.165 **
	(.01)	(.01)	(.01)	(.009)	(.009)
Hospital characteristics	NO	YES	YES	YES	YES
Insurance environment	NO	NO	YES	YES	YES
Demographic variables	NO	NO	NO	YES	YES
State dummies	NO	NO	NO	NO	YES
Obs.	26,760	26,760	26,760	26,760	26,760

Notes: Standard errors in parentheses. Elasticities evaluated at mean.

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Table 1.6: Marginal cost estimates

Output	**Estimate(US$)**
Inpatient Medicare discharges	10,324
Inpatient other discharges	8,203
Nursing home discharges	28,083
Outpatient visits	88

Note: marginal costs evaluated at mean.

Table 1.7: Estimation results with technology dummies

	(1)	(2)	(3)	(4)	(5)
Year 1997	.007	.008	.011 *	.006	.008
	(.005)	(.005)	(.005)	(.005)	(.005)
Year 1998	.014 *	.014 *	.013 *	.006	.014 *
	(.005)	(.005)	(.005)	(.005)	(.005)
Year 1999	.011 †	.014 *	.007	0	.015 *
	(.006)	(.005)	(.005)	(.005)	(.006)
Year 2000	.023 **	.033 **	.02 **	.01 †	.031 **
	(.006)	(.005)	(.005)	(.006)	(.006)
Year 2001	.025 **	.035 **	.02 **	.013 *	.033 **
	(.006)	(.005)	(.006)	(.006)	(.006)
Year 2002	.031 **	.04 **	.028 **	.021 **	.037 **
	(.006)	(.005)	(.006)	(.006)	(.006)
Year 2003	.049 **	.058 **	.044 **	.032 **	.047 **
	(.006)	(.005)	(.006)	(.006)	(.006)
Year 2004	.058 **	.067 **	.053 **	.043 **	.059 **
	(.006)	(.005)	(.006)	(.006)	(.006)
Year 2005	.068 **	.081 **	.066 **	.057 **	.074 **
	(.006)	(.006)	(.006)	(.006)	(.007)
Year 2006	.075 **	.085 **	.073 **	.064 **	.079 **
	(.006)	(.006)	(.006)	(.006)	(.007)
Year 2007	.081 **	.097 **	.08 **	.073 **	.091 **
	(.006)	(.006)	(.006)	(.007)	(.007)
$\sum_{i=1}^{I} \frac{\partial \ln VC}{\partial n_i}$	.393 **	.303 **	.3 **	.284 **	.237 **
	(.014)	(.014)	(.014)	(.014)	(.013)
$\partial \ln VC / \partial \ln K$	.336 **	.341 **	.333 **	.323 **	.321 **
	(.006)	(.006)	(.006)	(.006)	(.006)
Own-price: labor	-.162 **	-.191 **	-.202 **	-.212 **	-.234 **
	(.012)	(.012)	(.012)	(.012)	(.012)
Own-price: capital	-.126 **	-.148 **	-.157 **	-.165 **	-.182 **
	(.01)	(.009)	(.009)	(.009)	(.009)
Hospital characteristics	NO	YES	YES	YES	YES
Insurance environment	NO	NO	YES	YES	YES
Demographic variables	NO	NO	NO	YES	YES
State dummies	NO	NO	NO	NO	YES
Obs.	26,760	26,760	26,760	26,760	26,760

Notes: Standard errors in parentheses. Elasticities evaluated at mean.

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Table 1.8: Technologies pattern

	(+)		(-)	
Increasing trend	chthhos	(10/7)	ebcthos	(12/2)
	eswlhos	(10/0)		
	mrihos	(11/4)		
	tplnthos	(12/11)		
	traumhos	(12/2)		
Decreasing trend	cardhos	(12/11)	ultsnhos	(12/9)
	cclabhos	(10/8)		
	hemohos	(12/2)		
	msctghos	(12/7)		
	nichos	(12/4)		
	oncolhos	(12/6)		
	pethos	(11/1)		
Constant	aidshos	(10/1)	airbhos	(7/1)
	brnhos	(12/8)	bwththos	(12/1)
	dradfhos	(10/2)	cichos	(11/3)
	ffdmhos	(10/0)	ctscnhos	(10/7)
	msichos	(9/3)	vrcshos	(7/0)
	ortohos	(11/8)		
	pedichos	(12/11)		
	radthhos	(11/4)		
	robohos	(12/0)		
	specthos	(9/0)		
Mixed evidence	caoshos	(8/0)	mammshos	(7/3)
	petcthos	(6/0)	mscthos	(7/3)

Notes: Technologies under the plus (minus) sign report a majority of positive (negative) interactions. Increasing (Decreasing) trend corresponds to technologies with coefficients increasing (decreasing) in absolute terms through time. Constant refers to technologies without a clear pattern. Mixed evidence points out technologies whose effects reverse after some years. In parentheses the number of coefficients with prevailing sign is followed by the number of statistically significant ones.

1.10 Figures

Figure 1.1: Technology index (1996-2007)

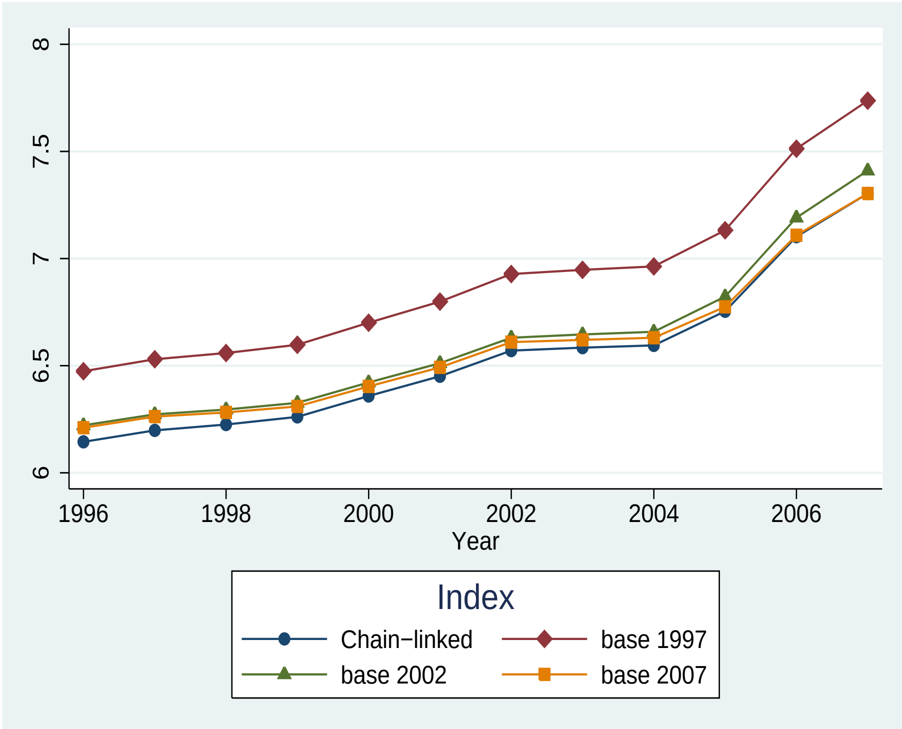
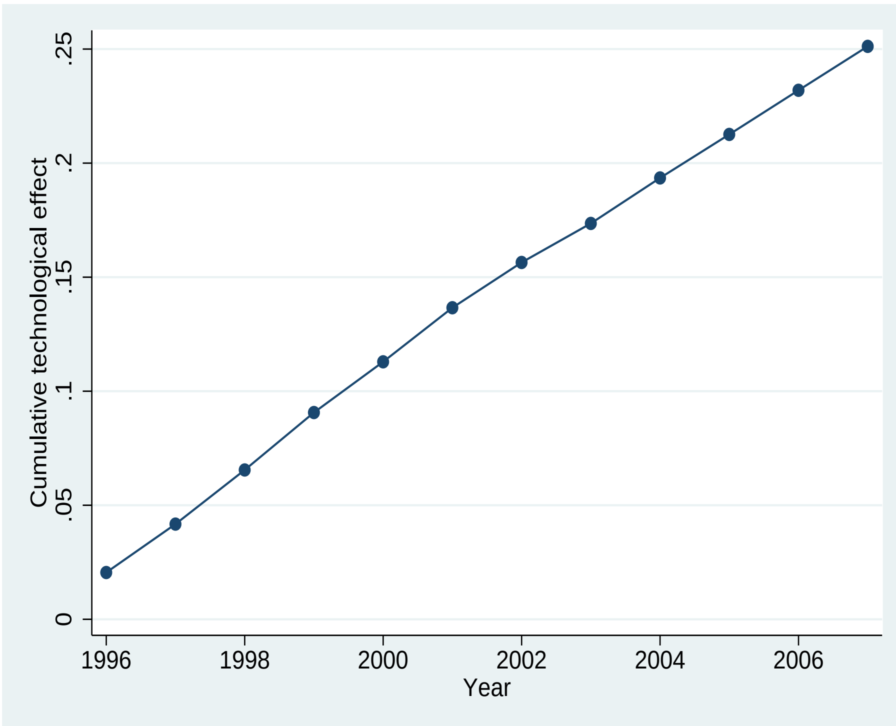


Figure 1.2: Cumulative technological effect (1996-2007)



Ten years of DRG reform. An empirical analysis of the influence of specialization, productive structure and ownership form on Italian hospitals technical efficiency.[12]

Abstract

We evaluate how the productive structure and level of specialization of a hospital affect technical efficiency by analyzing a six-year panel database (2000/2005) drawn from hospital discharge records and Ministry of Health data. We adopt a distance function approach, while measuring the technical efficiency level with stochastic frontier techniques. After controlling for environmental variables and hospital case-mix, inefficiency is negatively associated with specialization and positively associated with capitalization. Capitalization is typical of private structures which, on average, use resources less efficiently with respect to public and not-for-profit hospitals. Finally, by looking at scale elasticities, we find some evidence of unexploited economies of scale, leaving room for centralization.

[12] This paper is based on "Technical Efficiency, Specialization and Ownership Form: Evidences from a Pooling of Italian Hospitals." with Francesco D'Amico, published in *Journal of Productivity Analysis*, 32:203-216 (2009). We would like to thank: Vincenzo Atella and Federico Belotti for continuous and stimulating discussion; two anonymous referees; Giorgia Marini; the participants of the Sixteenth European Workshop on Econometrics and Health Economics and the Masterclass in applied Health Economics held in Bergen; the participants of the Econometrics PhD Students' seminars, held at University of Rome Tor Vergata; the participants of the Technical Efficiency Parallel Session at the Third Italian Congress of Econometrics and Empirical Economics, held at University of Ancona; and Hung-Jen Wang for the assistance with his new STATA package and for his suggestions concerning convergence of the models. We also thank Cristina Tamburini from the Ministry of Health for the data used throughout the paper.

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2.1 Introduction

The main objective of this paper is to evaluate how the productive structure and level of specialization of a hospital affect its technical efficiency. Here, we define productive structure as the degree of capitalization of the hospital, while the degree of specialization refers to the number of different types of cases treated within the organization. To this end, we report an economic analysis measuring the evolution of technical efficiency in hospitals located in the Italian region of Lazio in the 20002005 period. Subsequently, we assess the robustness of the hospitals optimizing behavior about 10 years after the introduction of the Diagnosis Related Group (DRG) system, and explore differences in efficiency as related to the hospitals ownership structure. Finally, we offer some insights as to how hospital scale of activity and productive conditions are determined by the institutional framework.

In Italy, the introduction of the DRG system in 1992 served both as a means of prospective payment and as an instrument for efficient allocation of resources. This should have made it possible to properly classify, measure, and assess hospitals performance by using industrial organization and management methods. Moreover the system applied to all organizations, independent of whether they were privately or publicly owned. As a consequence of the reform, hospitals were made responsible for their own outcomes, partially assuming the burden of financial risk. Further, budget constraints were made more binding for financing institutions, and this affected incentives to curb health consumption and production. As a result, two patterns emerged: on one hand, producers were encouraged to optimize their productive processes given the available inputs, and on the other hand, resource availability was reduced.

The theoretical industrial organization literature refers to several factors which might affect the level of technical efficiency reached by different ownership structures. Alas, there is no consensus regarding the net direction and size of these effects. Neoclassical theory advocates that nonprofits (both public and private) have a propensity to opt for administrators more interested in providing high-quality service than in producing profits. This type of hospitals might use more input to produce the same output as forprofit hospitals. Further, the presence of residual claimants should represent a powerful incentive to efficient production among for-profit hospitals (Alchian and Demsetz 1972). In addition to these neoclassical arguments, developments on a strand of economic literature that concentrates on information asymmetries have been used to provide a rationale for the existing differences in productive efficiency. While the lack of a residual claimant *á la* Alchian-Demsetz, might reduce managerial efforts and consequently having a negative impact on efficiency, the non-distribution constraint could represent an influential tool for controlling information asymmetries among diverse stakeholders (Hansmann 1996), increasing their efficiency by augmenting demand. Nonetheless, the impact of these characteristics on efficiency is still unclear.

The empirical literature on hospital efficiency in Italy consists of a substantial number of studies with a variety of methodologies, scopes, and results. Unexploited economies of scale are a recurrent theme (see Grassetti et al. 2005). Public hospital trusts (Aziende Ospedaliere, hereforeward referred to as AO) appear more efficient than other hospital types, such as acute-care and rehabilitation hospitals directly managed by local health authorities (Presidi Ospedalieri, ASLH),[13] but such a crystal clear difference is not observed in a comparison of public and private hospitals. Finally, technical efficiency seems to have decreased in the second half of the nineties, after the introduction of prospective payments under the DRG (see Barbetta et al. 2007).

Any analysis of hospital efficiency must take into account the so-called "Newhouse criticism" (Newhouse 1994). Model specifications are, in fact, generally restrictive: they omit some relevant inputs and outputs without taking into account the quality characteristics of the services provided. Further, hospital outputs are extremely heterogeneous. The number of discharged patients gives a rough measure of overall hospital production, if we do not take into account other aspects of treatment, such as the type and the severity of illness, the presence of other illnesses, the overall characteristics of the patient, and the like. We address these critiques by: (1) using hospital discharge records that allow to construct precise measures measures of output and controls of hospital case-mix; (2) representing technology with distance functions, which are more adequate than simple production functions in a multiinput multi-output setting. However, we acknowledge that this approach is still limited, since distance functions may be still mis-specificied. In absence of good measures of hospital quality, we decided not include the available indicators in our analysis and assessed that this does not invalidate our results. The paper is organized as follows: in the next section, we describe the econometric technique used for the estimation of efficiency scores. Subsequently, we present our data and provide some summary statistics, and in Sect. **??** we report the results. We conclude by commenting on our findings.

2.2 Stochastic distance functions

The notion of technical efficiency refers to producers' choices to allocate the resources at their disposal to obtain the maximum possible output from given inputs, or to use the minimum possible inputs in the production of a given level of outputs. Therefore, the analysis of technical efficiency may be defined as either output-oriented or inputoriented. When multiple inputs are used to produce multiple outputs, Shephard's distance functions (Shephard 1970) provide a characterization of the structure of production technology. Concept and properties of distance functions are well described in Kumbhakar and Lovell (2000), to whom we refer the reader. In what follows we have considered the number of discharges corrected for its case-mix complexity as final goods of the productive process. More than technical efficiency we are measuring what has been defined by Zweifel and Breyer (1997) "internal medical efficiency". However we are totally ignoring "external medical efficiency", or hospitals' effectiveness, defined as the ability of a hospital to improve the

[13]For a good and quick review of the different nature of these structures, see European Observatory of Health Care 2001

health status of a patient, for a given number of discharges or a given length of stay. A definition of output including external medical efficiency would be conceptually more accurate than the definition we use, but this would be empirically far more difficult to analyze, due to the lack of data reporting indicators of patients' health status following post-discharge recovery.

A general cross-sectional multiple-output stochastic frontier model can be written as

$$D^O(\mathbf{x}_i, \mathbf{y}_i, \mathbf{z}_i; \beta) = \exp(v_i - u_i) \tag{2.1}$$

where $D^O(\mathbf{x}_i, \mathbf{y}_i, \mathbf{z}_i; \beta)$ is the output distance function used to represent the distance from the frontier, which allows technological interactions across and among inputs and outputs. $\mathbf{y}_i$ represents the output vector of the i-th hospital, $\mathbf{x}_i$ is a vector of inputs and $\mathbf{z}_i$ is a vector of hospital specific characteristics other than inputs. β is the parameter vector which describes the structure of the technology. The error component is divided in two parts: v_i is an idiosyncratic normal term with zero mean, whereas u_i is a one-sided asymmetric negatively skewed distribution which captures inefficiency among observations. An analogous substitution relationship between factors and outputs showing deviations from the frontier is given by the input distance function

$$D^I(\mathbf{x}_i, \mathbf{y}_i, \mathbf{z}_i; \beta) = \exp(v_i - u_i) \tag{2.2}$$

2.1 and 2.2 can be rewritten as stochastic distance function models

$$1 = D^O(\mathbf{x}_i, \mathbf{y}_i, \mathbf{z}_i; \beta) \cdot \exp(u_i - v_i) \tag{2.3}$$
$$1 = D^I(\mathbf{x}_i, \mathbf{y}_i, \mathbf{z}_i; \beta) \cdot \exp(u_i - v_i) \tag{2.4}$$

The dependent variable in 2.3 and 2.4 is a constant, which has zero variance. Therefore in order to empirically estimate both equations we have to convert them into estimable models. This task can be accomplished by exploiting the fact that D^O is linear homogenous in outputs, while D^I in inputs, i.e.

$$D^O(\mathbf{x}_i, \omega\mathbf{y}_i, \mathbf{z}_i; \beta) = \omega D^O(\mathbf{x}_i, \mathbf{y}_i, \mathbf{z}_i; \beta) \qquad \forall\, \omega > 0 \tag{2.5}$$
$$D^I(\omega\mathbf{x}_i, \mathbf{y}_i, \mathbf{z}_i; \beta) = \omega D^I(\mathbf{x}_i, \mathbf{y}_i, \mathbf{z}_i; \beta) \qquad \forall\, \omega > 0 \tag{2.6}$$

As it has been pointed out by Lovell et al. (1994), one way of imposing such restriction is to normalize D^O and D^I respectively by one of the outputs and one of the inputs (so called "ratio" model), i.e.

$$D^O(\mathbf{x}_i, \mathbf{y}_i, \mathbf{z}_i; \beta)/y_{1i} = D^O(\mathbf{x}_i, \mathbf{y}_i^*, \mathbf{z}_i; \beta) \qquad \text{where } \mathbf{y}_i^* = \frac{\mathbf{y}_i}{y_{1i}} \tag{2.7}$$

$$D^I(\mathbf{x}_i, \mathbf{y}_i, \mathbf{z}_i; \beta)/x_{1i} = D^I(\mathbf{x}_i^*, \mathbf{y}_i, \mathbf{z}_i; \beta) \qquad \text{where } \mathbf{x}_i^* = \frac{\mathbf{x}_i}{x_{1i}} \tag{2.8}$$

which lead to

$$D^O(\mathbf{x}_i, \mathbf{y}_i, \mathbf{z}_i; \beta) = y_{1i} D^O\left(\mathbf{x}_i, \frac{\mathbf{y}_i}{y_{1i}}, \mathbf{z}_i; \beta\right) \tag{2.9}$$

$$D^I(\mathbf{x}_i, \mathbf{y}_i, \mathbf{z}_i; \beta) = x_{1i} D^I\left(\frac{\mathbf{x}_i}{x_{1i}}, \mathbf{y}_i, \mathbf{z}_i; \beta\right) \tag{2.10}$$

Substituting equalities 2.9 and 2.10 into equations 2.3 and 2.4 and dividing both sides respectively by y_{1i} and x_{1i} generates the following estimable composed error models

$$(y_{1i})^{-1} = D^O\left(\mathbf{x}_i, \frac{\mathbf{y}_i}{y_{1i}}, \mathbf{z}_i; \beta\right) \exp(u_i - v_i) \tag{2.11}$$

$$(x_{1i})^{-1} = D^I\left(\frac{\mathbf{x}_i}{x_{1i}}, \mathbf{y}_i, \mathbf{z}_i; \beta\right) \exp(u_i - v_i) \tag{2.12}$$

In the multi-output version of the model, the dependent variable is the reciprocal of the normalizing output, and the regressors are the inputs and the normalized outputs. Finally ui provides the basis for a reciprocal measure of output-oriented technical efficiency. Similar considerations applies for the multi-input case.

Some authors like Kumbhakar and Lovell (2000) have proposed the Euclidean norm of the outputs (or inputs) in order to respect the linear homogeneity restriction (so called "norm" model). In both the "norm" and "ratio" model there is an issue of endogeneity bias, since normalized outputs and inputs appearing as regressors may not be exogenous. Some authors like Coelli and Perelman (1967) or Morrison et al. (2000) argue the normalization y_i/y_{mi} creates an output mix vector that is more likely to be exogenous than either y_i or $y_i/|y_i|$. It is not the objective of the paper to enter into this debate. For practical purposes we preferred the "ratio" model, since normalizing by the norm of the outputs increases considerably the degree of multicollinearity, due to the introduction of exact linear dependencies.

Note that while modelling multiple-input, multipleoutput technologies we have to restrictively assume that the disturbance terms affect the output vector y multiplicatively, i.e., all outputs are assumed to be proportionally affected by the same disturbance.

Three major drawbacks affect cross-sectional stochastic frontier models:

1. Estimations strongly rely on distributional assumptions on each error component.
2. Technical (cost) inefficiency might be correlated with the regressors.

3. Technical and cost efficiency cannot be consistently estimated, because the variance of the conditional mean or mode does not go to zero as the sample size increase.

2.3 Data and summary statistics

We analyze data provided by the public health agency (PHA) of the Lazio region consisting of hospital discharge records (HDRs). Hospitals' administrators have to fill out HDR according to law as informative tool over which to base patients admission financing. In each HDR, data concerning the patient are recorded. Beyond vital statistics, we observe health-related information collected during the patients internment including date of admission and discharge, date of surgery, surgery type, transfers to other hospitals, and the like. Further, we observe the DRG related to each patient and its weight, i.e., the level of complexity. Generally, the number of discharges is strongly correlated with the sum of DRG weights, and this is supported by our dataset. However when we focus on groups of more complex cases, this correlation may be lower. This, for example, is what typically is observed in hospitals with emergency rooms. Generally studies of hospital efficiency do not have such disaggregated data at disposal and are forced to use all discharges or admissions adjusted by a measure of complexity. Therefore, the observation of the DRG weight is extremely important since it not only makes it possible to capture the precise number of treated cases, but also provides a measure of case-mix control for each output.

The aggregation of the DRGs followed a classification system which is commonly used at an international level, and which has already been applied to Italian data (see Fabbri 2003). Within this classification, hospital activity may be summarized in 28 production categories. These are made up of DRG groups consistent with a standard of productive homogeneity.[14] In order to make the model empirically more manageable, we have further aggregated these 28 lines into the following groups: complex surgery, emergency room treatments, cancers and HIV, general medicine, and general surgery.

As far as the measurement of output is concerned, frontier techniques seem to work best when the product is homogeneous and one-dimensional such as, for instance, kilowatt-hours in the electricity industry. This is not the case for hospital care, which exhibits wide variation in the quality of the product and its dimensionality, both on the input and the output sides. Therefore, it would be possible that productive units being assessed might not use the same technologies. In order to control at least partially for these types of differences, we have restricted our focus to acute patients. Acute care refers to the necessary treatment of a disease for a short period of time in which a patient is treated for a brief but severe episode of illness. The goal of the hospital is to discharge the patient as soon as he or she is deemed sufficiently healthy and stable following the critical

[14] A hospital is basically viewed as a human service enterprise whose primary function is the provision of diagnostic and therapeutic medical services. Production lines are specific sets of services provided to individual patients and largely coincide with an appropriate definition of treatments within each ward typology.

period. Acute care differs from longterm care and rehabilitation care, which are characterized by a combination of treatments provided once the acute phase of the disease has been overcome. These treatments aim to stabilize the disease towards two possible outcomes: recovery or management of a chronic condition.

Hospitals devoting their activity exclusively to longterm and/or rehabilitation care, therefore, have very different production functions from acute-care hospitals, which would make the two groups impossible to compare. For this reason, we did not include such hospitals in the sample. For those hospitals dedicated only partially to postacute care, we did not include the DRG weights from postacute care activities in any of the output aggregates. Relatedly, when hospital activity is limited to the treatment of acute patients, this simplifies the debate as to whether the variable measuring output should be the number of discharges or the number of inpatient days. The latter variable may more heavily reflect the assistance component of hospital production, which is unique to structures dedicated to long-term care and rehabilitation, and hence it may reflect a productive choice of the hospital rather than the hospitals efficiency level.[15]

We obtained data concerning inputs from the Italian Ministry of Health. These included: number of beds as a rough measure of capital and number of physicians, nurses and other personnel (teaching plus ancillary staff) as a measure of labor. By classifying labor into different categorieswe recognized differing skill requirements. We are aware that number of hours workedmay 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.[16]

As mentioned above in discussing the measure of outputs, some hospitals undertake both acute and post-acute care activity. Therefore, for consistency, we must eliminate this element from the inputs. For the bed variable, this exclusion was straightforward, since we received data on beds for rehabilitation and long-term care. However, hospital staff numbers 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 and to provide 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-forprofit 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

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

[16]We attempted to use an index of hospital machineries as a more refined measure of capital, attaching their average costs as a weight. However the set of known costs is incomplete, and even if this missing data concerns only a couple of machines, we believe this might bias the index value. This may affect parameter estimates, as happened in most of the adopted model specifications.

excluding those hospitals which did not sign any type of agreement with the National Health System (NHS) and are exclusively devoted to a “pure” forprofit activity. We feel that including activities which are not funded by the NHS would induce an important discrepancy with the other two hospital categories. Furthermore, not funded admissions belong to a peculiar category: those normally include more amenities (e.g. hotel-type facilities) and/or might require a more intense use of non medical personnel. All of these differences might be hard to be taken under control. For the sake of consistency, for private hospitals we included in our sample 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).

This gives us a final sample of a weakly balanced panel of 108 hospitals of the Lazio region observed during the years 2000/2005, which sums 625 observations. In Table 2.1 we show the distribution of the hospitals and acute patients per year, and with respect to ownership structure. From the combined reading of input and output statistics (Table 2.2), it appears private hospitals are smaller with respect to all size-related measures: fewer beds and personnel, and a lower sum of DRG weights. Further, they are specialized and concentrated on less complex cases, as can be seen, for instance, by the low number of emergency room treatments. This appearance is confirmed by the hospital specialization index we have computed. Formally, for the h-th hospital, the Gini ratio is equal to

$$\texttt{gini}_h = \frac{\sum_{i=1}^{N-1}(p_i - q_i)}{\sum_{i=1}^{N-1} p_i}, \qquad i = 1, 2, \ldots, N \tag{2.13}$$

where N is equal to 20, the total number of existing Major Diagnostic Categories (MDC), q_i is the fraction of the total discharges treated by the first i MDCs, while p_i is the ratio of the number of the i-th MDC over the total number of MDCs. The index varies between 0 and 1: it is equal to zero in case of perfect equidistribution (polispecialistic medical center), since all the differences $p_i - q_i$ are null. Meanwhile it is equal to one in case of maximum specialization, since equation (2.13) boils down to quantity $\sum p_i / \sum p_i = 1$.

The Gini ratio may be computed by using DRGs instead of MDCs and in this case N of equation (2.13) would equal 489, the total numebr of existing DRGs. Counting the number of DRGs for this measure of specialization would be more appropriate, since it better captures the range of all hospital production. However due to the fact that hospitals tend to focus on more remunerative and less costly practices, the array of DRGs chosen by hospitals tends to be very narrow. Therefore the index of specialization is very high for all hospitals and on average it is similar for all ownership categories. In order to get a variable with a greater and more significative range of variation, we use as MDCs, where diagnoses correspond to a single organ system or etiology and are associated with a particular medical specialty.[17] We notice how public and not-for-profit hospitals' activity

[17] Farley and Hogan (1990) made an in-depth analysis of hospital specialization measures. They proposed an

has increased through our observational period (the last two years show a reduced amount due to some dropouts in the number of the hospitals included). Private hospitals activity results on average more stable. Such a global phenomenon was probably induced by the converse reduction of the lenght of stay, which started after the introduction of the DRG system in Italy. The effects of the new system have progressively optimized through time the length of hospital inpatient care.

2.4 Empirical implementation

The models

The functional form of $f(\cdot)$ may take different aspects. With a Cobb-Douglas specification we can interpret coefficients as output elasticities, since the covariates are all expressed in logs. In this application however we cannot estimate this log-linear function, since in a distance function context, Cobb-Douglas has the wrong curvature in the $\frac{\mathbf{y}_i}{y_{1i}}$ and $\frac{\mathbf{x}_i}{x_{1i}}$ spaces. Therefore we have estimated a translog function, where the presence of squared and interaction terms gives a high degree of flexibility.

For the multi-output multi-input stochastic frontier consider the two following models

$$\begin{aligned} -\ln y_{1i} &= \beta_0 + \sum_{m=1}^{M} \alpha_m \ln y^*_{mi} + \sum_{k=1}^{K} \beta_k \ln x_{ki} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{N} \alpha_{mn} \ln y^*_{mi} \ln y^*_{ni} + \\ &+ \frac{1}{2}\sum_{k=1}^{K}\sum_{j=1}^{J} \beta_{kj} \ln x_{ki} \ln x_{ji} + \sum_{k=1}^{K}\sum_{m=1}^{M} \beta_k \alpha_m \ln x_{ki} \ln y^*_{mi} + \sum_{h=1}^{H} z_h + v_i - u_i \end{aligned} \tag{2.14}$$

$$\begin{aligned} -\ln x_{1i} &= \beta_0 + \sum_{k=1}^{K} \beta_k \ln x^*_{ki} + \sum_{m=1}^{M} \alpha_m \ln y_{mi} + \frac{1}{2}\sum_{k=1}^{K}\sum_{j=1}^{J} \beta_{kj} \ln x^*_{ki} \ln x^*_{ji} + \\ &+ \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{N} \alpha_{mn} \ln y_{mi} \ln y_{ni} + \sum_{m=1}^{M}\sum_{k=1}^{K} \beta_k \alpha_m \ln x^*_{ki} \ln y_{mi} + \sum_{h=1}^{H} z_h + v_i - u_i \end{aligned} \tag{2.15}$$

where in both models i denotes hospital, k, j denote inputs, m, n denote outputs, and h denotes shifting factors. y_{mi} is the m-th output variable for hospital i and a symmetry constraint has been imposed on the interaction terms, i.e. $\alpha_{mn} = \alpha_{nm}$. Further x_{ik} is the k-th input variable for hospital i and a symmetry constraint has been imposed on the interaction terms, i.e. $\beta_{kj} = \beta_{jk}$.[18]

Information Theory Index, where specialization is given by caseload deviation from that of the typical hospital. The main pitfall of this Information Theory Index is therefore its inability to distinguish between hospitals that treat either a very narrow or a very broad range of cases, since both will tend to have relatively high index values. Hence, we decided to make use only of the Gini ratio.

[18]Note that each input and output variable has been standardized with its median.

In model 2.14 y_{1i} is the output used for normalization, which is given by the sum of the DRG weights of the discharges in complex surgery. On the other hand in model 2.15 the number of beds, x_{1i}, is the input used for normalization. Since we treat the z_h factors as fixed effects, this translog function is not fully flexible. In addition to input variables we included

- Time dummies for each year of the sample, using 2000 as the base year. Using a set of time dummy variables is the same as running time fixed effects without considering panel effects.
- Two variables concerning ownership: one dummy if the hospital is private and another one if the hospitals is NFP, i.e. if it has been assimilated to a public structure. "Fully" public hospitals represent the base category.[19]
- Geographical dummies for each ASL. For the county of Rome we distinguished between hospitals directly managed by Local Health Authorities (`Rome-asl`) and self-managed hospitals (`Rome-self`).

Before getting into the details of the model and commenting the results we would like to remark that our estimations were based exclusively on a pooling of data. That is, we treated the observations as part of a single cross-section. The reasons are explained through a simple decomposition of the total sum of squares (SST). For a generic variable z_{it} observed for hospital i at time t, SST is equal to the sum of the between hospitals sum of squares, SSB(i), and the within hospitals sum of squares, SSW(i), i.e.

$$\begin{aligned} SST &= SSB(i) + SSW(i) \\ SST &= \sum_i \sum_t (z_{it} - z_{..})^2 \\ SSB(i) &= \sum_i (z_{i.} - z_{..})^2 \\ SSW(i) &= \sum_i \sum_t (z_{it} - z_{i.})^2 \end{aligned}$$

where $z_{..}$ is the global mean and $z_{i.}$ denotes the average of z_{it} over t. To standardize the results we divide $SSB(i)$ and $SSW(i)$ by SST in order to calculate the percentage of both components. Since most of the variation in the input and output variables is between rather than within the hospitals it seems there is very little panel data variation in the sample, which is similar to a cross-section.

[19] Public hospitals include hospitals directly managed by ASL and AOs. Hospitals assimilated to public structures are the following: 1) "Istituto qualificato presidio della USL"; 2) "Istituto di Ricovero e Cura a Carattere Scientifico (IRCCS)"; 3) "Ospedali classificati o assimilati ai sensi dell'art.1 u.c. L.132/68"; 4) "Policlinici Universitari".

Estimates' results

As a first step of our analysis, we ran a pooled OLS regression in order to provide a simple test for the presence of technical inefficiency in the data. If there were no technical inefficiency, the error term would be symmetric (being $u_i = 0$, then $\epsilon_i = v_i$) and the data would not support a technical inefficiency story. A skewness/kurtosis test for normality (results not shown) rejected the null hypothesis of normal residuals. Hence, it seems there is evidence of the presence of inefficiency in the data.

The second stage consisted of a general-to-specific estimation and test approach. In order to estimate technology parameters and technical efficiency we added the following set of assumptions:

$$v_i \sim \mathcal{N}(0, \sigma^2_{v_i}) \tag{2.16}$$

$$u_i \sim \mathcal{N}^+(\mu_{it}, \sigma^2_{u_i}) \tag{2.17}$$

$$\mu_i = \mathbf{q}_i\phi \tag{2.18}$$

$$\sigma^2_{v_i} = \exp(\mathbf{w}_i\delta_i) \tag{2.19}$$

$$\sigma^2_{u_i} = \exp(\mathbf{t}_i\gamma_i) \tag{2.20}$$

Equation 2.16 and 2.17 tell us the variance of the idiosyncratic error term and the variability of the inefficiency term are not constant. These have been modelled in equations 2.19 and 2.20 respectively. Further by using the truncated normal distribution for the inefficiency term u_i we can parameterize its mean μ. We must note that seeking to address the problem of heteroscedasticity by parameterizing the variance of the inefficiency error term and parameterizing the mean of the truncated normal distribution (thus changing its shape) can be seen as another approach to study the exogenous effects on inefficiency, as has been pointed out by Kumbhakar and Lovell (2000). Degree of competitive pressures, managerial characteristics or even ownership form may influence the structure of the technology by which conventional inputs are converted to outputs or may influence the efficiency with which inputs are converted to outputs. Moreover this particular combination of distributional assumptions allows us to accomodate non-monotonic efficiency effects. This implies that variables having such relationship can be positively related in part of the parameter space while negatively related in the rest (see Wang 2002 for more details). Last but not least, Wang and Schmidt (2002) have demonstrated that this model specification allows one-step estimation of the parameters, avoiding two-step procedures which give biased results if the model estimated at the first step is misspecified. Further they note that the vector of variables affecting the frontier may overlap the vector of variables affecting technical efficiency.

In this paper we are intended to study the impact of specialization and capitalization on hospital efficiency. Therefore we have included for both models in equation (2.18) the Gini ratio (`Gini`) as proxy for specialization and the nurses per bed ratio (`Nurses/Bed`) as proxy for capitalization. This latter variable has been already used as determinant of cost efficiency in previous studies. Farsi and Filippini (2006) showed that a higher nurses per bed ratio decreases efficiency, indicating that quality of care is costly. For both models, we have subsequently added another common inefficiency determinant representing hospital dimensions: the logarithm of beds (`Beds`) in the output-oriented model and the logarithm of the sum of weights for acute patients (`Weighted Patients`) in the input-oriented model. Further, in the input distance function model, we achieved a better fit by adding the mean age of the patients (`Age`) to explain mean inefficiency. We assumed the sources of idiosyncratic noise vary in both models with the hospital size, with `Beds` and `Weighted Patients` again serving as a proxy for this variable. Finally, in the output model, we assumed hospital dimensions affected the variability of the inefficiency term.

We implemented some general likelihood ratio (LR) tests, while posing restrictions on the unrestricted translog model, in order to get to a "preferred" model. The LR test is given by $\lambda = 2(\ln \mathcal{L}_1 - \ln \mathcal{L}_0)$, where $\ln \mathcal{L}_0$ and $\ln \mathcal{L}_1$ denote the maximum log-likelihood value under the null hypothesis H_0 and the alternative H_1, respectively. The LR tests conducted are presented in Table 2.3. For both models, the first two null hypothesis assessed the appropriateness of using the half-normal distribution ($\mu_i = 0$), with and without modelling heteroscedasticity. We then tested the importance of modelling the variance of the error terms ($\mathbf{w}_i = 0, \mathbf{t}_i = 0$). Finally we tested whether exogenous inefficiency variables, as a group, have a significant impact on technical inefficiency. All these hypothesis were strongly rejected. More generally we can say that we cannot do without unmodeled heteroscedasticity in the error components and nor without modelling the mean of the inefficiency error term.

In table 2.4 we show scale and input/output 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. Standard errors were computed by applying the delta method to linearize the elasticity functions around the estimated parameter values and then using standard formulas for the variances and covariances of linear functions of random variables. The results given in table 2.4 suggest significant increasing returns to scale for both models, since scale elasticities $\epsilon_{\mathbf{y},\mathbf{x}} > 1$ and $\epsilon_{\mathbf{x},\mathbf{y}} < 1$ and the null hypothesis of constant returns to scale is rejected. From an administrative point of view, this is the typical situation where there is an incentive to centralize operations.

The individual input and output elasticities underlying the scale elasticities are also provided. In the output distance model, elasticity for nurses and beds is high while the marginal product of other staff labor is slightly negative, even if not statistically significant. Therefore it seems there is some excess in the size of the group of workers with administrative and technical duties. Moreover from the input-oriented model we can see that all marginal costs, except from ER treatments, are positive and that not surprisingly general medicine (Y5) and general surgery (Y4) are the outputs primarily contributing to input use.

Focusing on existing differences among ownership structures, which we do not report here, scale elasticity varies a great deal between hospitals, and is greater for private hospitals and lower for NFP structures in both models. However this is not surprising, and may simply reflect the existence of ceilings on fee-for-service financing, which have been introduced in Lazio region. The main difference between public and NFP hospitals and private structures is that the latter cannot surpass fixed volume limits, while the former are at least reimbursed at a reduced rate once having reached the ceiling, or may even be fully reimbursed because of the political necessity of avoiding hospital failures. Therefore, a possible effect of this different treatment is input-minimizing behavior in private structures, which are forced to work at a reduced scale. Further, private units are slightly over-capitalized with respect to nursing staff, while public and more heavily NFP hospitals have a slight excess of administrative and technical staff , suggesting the opportunity for a re-allocation of resources within these structures.

In table 2.5 we show maximum likelihood estimates of the remaining parameters of the hybrid translog production functions, other than technology parameters. We also show the equations of the two heteroscedasticity terms and the mean of the inefficiency term. With respect to ownership, the coefficient for NFP hospitals is always significant (at least at a 10% level) with a positive sign.[20] The role played by private hospitals is, in contrast, less straightforward. They positively and significantly contribute to an upward shift of the frontier in the input-oriented model but the sign is reversed in the output model, even though it is not statistically significant. Time dummies show a positive trend, with ever-increasing coefficient values, and are not significant only for the first two years of the output distance model. It might be interpreted that we are capturing a linear time trend or disembodied technical change. As far as geographical dummies are concerned, the base category is represented by the hospitals in the county of Rome, but not within this municipality. It appears that hospitals in all the other counties, except those self-managed hospitals located in Rome, contribute to an upward shift of the frontier.

Regarding the determinants of the mean of the inefficiency error term, for the input model, mean age is positively correlated with inefficiency, while for both models size measures, capitalization and specialization are instead negatively correlated. Particularly, nurses per bed and gini are 1% significant in the input model, but only at 5% and 10% in the output distance model respectively. The result obtained for specialization is strengthened if we look at the sign of cross-output terms (see table 2.6), that allow us to evaluate input and output complementarities. From the input specification we observe that only three cross-output terms over ten are negative, two of them being significant.[21] The absence of output jointness is not a proof of pro-efficiency specialization,

[20]Remember that for a correct interpretation, the sign in the distance functions must be reversed. This implies that in the output distance model, the upward shift of the frontier is given by a negative sign. While for an input distance function by a positive sign.

[21]We remind that signs and magnitudes of the cross-effects represent input/output jointness. In the input specifi-

but a fact that is consistent with this hypothesis.

Before commenting on efficiency results we would like to remark that in our models we have attempted to control for quality. This can be broadly divided into outcome and structural indicators. With respect to the outcome indicators, we have computed readmission and mortality rates as quality adjustments or scaling factors for output measures. As noted by Milne and Clarke (1990), both indicators have big drawbacks. Further we did not feel confident with using readmission rates, since we could not distinguish between patients with planned vs. unplanned readmission. Hence the computed rate depends subjectively only on the number of days used as threshold. Mortality rates, in contrast, were easily measured, but their impact on the estimation is negligible, likely due to the fact that they are very rare across inpatient specialties.

For structural measures of quality, we tried including the teaching status of the hospitals in the frontier of both models, using the number of teaching staff as a proxy, and an attraction index, proxied by the rate of discharges of people coming from a different ASLH. Signs were not significant, and efficiency estimates with and without these variables were highly correlated. Hence, we decided not to include them in the models. It is therefore possible that without being able to properly account for quality our estimates may suffer from omitted variable bias. However as Rosko and Mutter (2008) pointed out, these omissions may not be as serious as commonly thought.

Technical efficiency: trends and transitions

In figure 2.1 we show estimated sample mean efficiencies for each hospital ownership category. In the output distance model, public and NFP hospitals are on average more efficient than the accredited private ones. We observe a decline in technical efficiency over time for NFP hospitals, and a smaller reduction for private ones, while public hospitals seem to remain at a roughly constant efficiency level throughout the period. In order to explain such differences, as we mentioned in the discussion of scale elasticities, private hospitals have a legal limit to the maximum output they can produce for the NHS. This fact, coupled with the different and penalizing reimbursement rate among hospital types, not only induced distortions in the production scale, but also in the efficiency level. This meaning that private hospitals would have actually room for more activity, but that this is hindered by the legal limit for funded admissions. Since this limit is yearly varying, for private hospitals might be problematic to make their inputs size fitting with it, conducting to a general over proportioning. In case privates hospitals had a better quality performance, this could at least partially explain the efficiency gap. However, we do not have any clue for assessing that private and non private hospitals work at a different quality level, ceteris paribus the DRG. In case, we could expect a better performance from public or not-for-profit structures which, working at larger scales, benefit of greater learning processes.

cation negative cross-output terms represent output jointness, while in the output specification positive cross-input effects imply input complementarities.

Looking again at figure 2.1, we may note that, in the input distance model, the three ownership categories are much closer to each other and all show an increase in efficiency patterns over time. Public hospitals at the end of the period show a slight reduction, converging to NFP averages, while private structures are now at the same level of the other categories. These results do not contradict the output distance model, since we are estimating two different frontiers under two different sets of theoretical assumptions. With the input distance function we are assuming a cost-minimizing behavior of the hospital, which chooses an input vector, evaluated at exogenously determined input prices, that minimizes the cost of producing a given output vector. This assumption clearly is valid if the hospital acquires inputs in competitive markets. The behavioral assumption we are making through the output distance function is that the firm chooses an output vector that maximizes revenue at given output prices for a given input vector. The plausibility of this assumption is linked to the sale of outputs in competitive markets.

In this study, neither assumption is strictly respected. In fact, none of these models is perfectly congruent with the present incentive framework within the NHS. With a simplifying assumption, we may believe private and NFP hospitals try to minimize costs and hence aim at reducing the use of inputs. In such a context, where we have to take into account mechanisms of control over output volumes, an input-oriented model is preferable. Contrastingly, public hospitals seem to have more discretion with respect to their level of production. Therefore an output-oriented model cannot be discarded a priori, since it shifts the focus from costs to revenues.

In figure 2.2 the horizontal and the vertical axis represent efficiency levels for all the hospitals respectively in 2000 and 2005. For the output distance model there is more mobility in technical efficiency over time. This does not happen in the input distance case, but this may be due to greater stability in input endowments. In each of the two models, at the maximum values of the distribution, distances from the 45° line are not very large, implying stability over time for the estimated efficiencies. In the input distance case, apart from a few observations, this happens for the full range of the efficiency distribution. Furthermore, if we look carefully at both graphs, we can see that the majority of public hospitals passes the 45° line, indicating an increase in technical efficiency. This confirms what emerged from the graphs of the efficiency trends.

In tables 7(a) and 7(b) we show transition matrices from 2000 and 2005 for our model specifications. These tables confirm that a significant percentage of the hospitals belonging to the extreme quintiles of the technical efficiency distribution in 2000 still belongs to the same quintile in 2005. The diagonal elements of the transition matrix show more mobility. As expected, those diagonal elements are "fatter" when considering shifts year-by-year (data not shown). The fact that individual hospital units tend to remain in the same or close to the same quintile of the efficiency distribution is not a surprise. In fact, we do not expect hospitals to change dramatically their operational behavior in a so short a time period, or year by year.

Capital-labor distribution

In our estimates, we have found a wide distribution of technical efficiencies. We attempted to ascertain whether productive structures are related to efficiency values, in order to make our analysis more precise in distinguishing among heterogeneous units. In fact, since our dataset contains the entire population of Lazio's hospitals, we have very different units in terms of size and kind of activity. Although we have partially purged heterogeneity by using control variables for ownership type, time and location, using only observations related to acute patients, in a flexible model context that allows also for heteroscedasticity, these measures seem not to have eliminated all the possible sources of diversity from the dataset. Our idea was to draw a curve corresponding to the efficiency frontier. We made a scatter-plot of dots corresponding to the position of each hospital. In particular, the estimated efficiency determined the distance between the unit and the frontier in the graph. The radial-position is fixed depending on the capital-labor ratio value. The polar coordinates are given by the couple:

$$\left[\cos\left(\arctan\left(\frac{K_i}{L_i}\right)\right) \times TE_i \;\;,\;\; \sin\left(\arctan\left(\frac{K_i}{L_i}\right)\right) \times TE_i\right]$$

where the technical efficiency level of the i-th hospital $TE_i \leq 1$ if it lies below or on the frontier curve. This kind of figure has the advantage of pointing out how estimated efficiencies vary among different capital-labor ratios and gives the possibility to distinguish particular typologies of units.

Specifically we differentiated hospitals among ownership structures for both models (figure 2.3). At first glance, we may notice that private and public structures seem to sort into two different "cones" of capital-labor ratio, while NFP hospitals appear to be more evenly spread. Cones exclude outliers for both categories, i.e. they do not include hospitals below the tenth percentile or above the ninetieth percentile of the capital-labor ratio. Further there appears to be an inverse relationship between the capital-labor ratio and technical efficiency. This evidence has been already captured in the frontier estimation, where the nurse-per-bed ratio is negatively correlated with inefficiency. The more capitalized the hospital, as is the case for private hospitals, the less efficient it appears to be.

It seems reasonable that units operating with different productivity structures cannot be directly compared. The capital-labor ratio is indeed quite variable among the different structures. We tried to define the labor factor in different ways, in order to verify whether the definition made a difference. In particular, we used three typologies of labor aggregation: the first one was the simple sum of all workers operating in the structure; the second was the simple sum of physicians and nurses operating in the hospital; and the last corresponded to a sum of five categories of workers, weighted by their estimated wage. For estimating wages we gleaned data from AOs' balance sheets, taking the total amount of salaries divided by the number of workers for each of three categories (physicians, nurses and other staff). The only labor definition which widens the spread of hospitals in the graph is the sum of physicians and nurses. However, in each of the three cases, the relative proportions are nearly the same.

Another question arises: what are the causes of relatively lower labor usage in private hospitals and higher usage in public ones? We believe that public hospitals operate in a more rigid institutional framework, inclined to keep a high number of workers, while private ones do not. Given that the latter face greater economic risk, it is reasonable to assume that they decide to turn this risk toward workers, instead of toward capital (meaning medical equipment with related costs). Another explanation from the public finance literature is that one role of public institutions is to provide employment. This phenomenon causes a high value for the capital-labor ratio in private structures, but according to our evidence, seems to penalize technical efficiency.

2.5 Conclusions

In this paper, we studied the productive process of the hospitals of the Lazio region by means of an economic analysis. We used data from the hospital discharge records provided by the Public Health Agency of Lazio in order to derive measures of output, such as the number of discharged patients. Further, from the Ministry of Health we obtained data concerning labor and capital used as inputs. Our study has been limited to the pooled cross-section case, since a simple sum of squares analysis showed very little panel variation in the sample.

OLS residuals analysis showed the presence of inefficiency in the data. Subsequently, we implemented a stochastic frontier analysis to assess the level of technical efficiency achieved by the hospitals. When deriving technology parameters, we took into account case-mix complexity. With this correction of the left hand-side of the frontier equation, we were able to address one of the main points of Newhouse's critique, i.e. the impossibility of assessing hospital production by means of efficiency analysis tools, because of excessive simplification of the productive process, especially with respect to the quality of services.

Inefficiency is negatively associated with specialization and positively with capitalization. Capitalization is typical of private hospital structures which, on average, make a less efficient use of resources when compared to public and not-for-profit hospitals. As far as the productive structure of the hospital is concerned, there seem to be increasing returns to scale, suggesting centralization of operations. Private units work in slightly over-staffed conditions for medical staff, while public and more heavily NFP hospitals do the same for technical and administrative staff, suggesting the opportunity for a re-allocation of resources within these structures.

Our efficiency estimates are strictly related to the choice of a specific model, which depends on the theoretical and empirical assumptions one is willing to make. The input distance function model is based on a cost-minimization hypothesis, and empirically is more appropriate in studying private and NFP hospital behavior. Meanwhile, the output distance function is based on a revenue-maximization hypothesis and is more appropriate to the study of public hospital patterns. Being aware of the limitations of the model, we tried to paint a picture from the combined reading of both.

The results suggest that public and NFP hospitals make a more efficient use of resources. In fact the level of the estimated mean technical efficiency appears to be significantly higher than that of private structures in the output-oriented model, and slightly higher in the input-oriented model. This large gap in the former model can be attributed to the different reimbursement rates among ownership categories. This turned out to be the cause of under-sizing even in private structures. Whether the funded activity limitations for the latter were softened, this could result in an improvement of the private hospitals' efficiency. Naturally, such a policy change is always subject to the availability of public financial resources.

Finally, the minor differences in efficiency levels reported in the input-oriented model, on the other hand, are more easily explainable as a result of the cost-minimizing assumption upon which the model is based.

2.6 References

Alchian A., H. Demsetz (1972) "Production, information costs, and economic organization", *Amer. Econ. Rev.*, **62(5)**: 777-795.

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

Coelli, T. and S. Perelman (2000) "Technical efficiency of European railways: a distance function approach", *Appl. Econ.*, **32**: 1967-1976.

European Observatory of Health Care Systems (2001) Health Care Systems in Transition - Italy, `http://www.euro.who.int/document/e73096.pdf`.

Fabbri D. (2003) "L'efficienza tecnica e di scala degli ospedali pubblici in Italia", in L'efficienza dei servizi pubblici, Banca d'Italia.

Farley, D.E. and C. Hogan (1990) "Case-mix Specialization in the Market for Hospital Services", *Health Services Res.*, **25(5)**: 757-783.

Farsi, M. and M. Filippini (2006) "An analysis of efficiency and productivity in Swiss hospitals", *Swiss Journ. Econ. Stat.*, **142(1)**: 1-37.

Grassetti, L., E. Gori and S. Minotti (2005) "Multilevel flexible specification of the production function in health economics", *IMA Journal of Management Mathematics*, **16(4)**: 383-398.

Hansmann H. (1996) The Ownership of Enterprise, Harvard University Press: Cambridge, MA.

Kumbhakar S.C. and C.A. Lovell (2000) Stochastic Frontier Analysis, Cambridge University Press.

Lovell, C.A.K., S. Richardson, P. Travers and L.L. Wood (1994) "Resources and functioning: a new view of inequality in Australia" in *Models and measurement of welfare and inequality*, eds. W. Eichhorn, Springer, Berlin.

Milne, R. and A. Clarke (1990) "Can readmission rates be used as an outcome indicator?", *Br. Med. Journ.*,**301**: 1139-1140.

Morrison, C.J., W.E. Johnston and G. Frengley (2000) "Efficiency in New Zealand sheep and beef farming: the impacts of regulatory reform", *Rev. Econ. Stats.*,**82**: 325-337.

Newhouse, J.P. (1994) "Frontier estimation: How useful a tool for health economics?", *J. Health Econ.*, **13**: 317-322.

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

Rosko, M.D. and R.L. Mutter (2008) "Stochastic frontier analysis of hospital inefficiency. A review of empirical issues and an assesment of robustness", *Medical Care Research and Review*, **165:2**: 131-166.

Shephard, R.W. (1970) The theory of cost and production functions, Princeton University Press.

Wang, H. (2002) "Heteroscedasticity and non-monotonic efficiency effects of a stochastic frontier model", *J. Productiv. Anal.*, **18**: 241-253.

Wang, H. and P. Schmidt (2002) “One-step and two-step estimation of the effects of exogenous variables on technical efficiency levels”, *J. Productiv. Anal.*, **18**: 129-144.

Zweifel, P. and F. Breyer (1997) Health Economics, Oxford University Press.

2.7 Tables

Table 2.1: Number of hospitals and acute patients by year and ownership type

(a) Hospitals

Year	Public	NFP	Private	Total
2000	49	16	40	105
2001	49	16	38	103
2002	50	17	38	105
2003	52	17	39	108
2004	49	17	39	105
2005	45	18	36	99
Total	294	101	230	625

(b) Acute Patients

Year	Public	NFP	Private	Total
2000	502,960	356,543	134,291	993,794
2001	507,771	378,632	138,035	1,024,438
2002	524,445	411,879	140,125	1,076,449
2003	540,208	427,752	152,219	1,120,179
2004	536,407	452,790	163,419	1,152,616
2005	520,596	487,316	175,097	1,183,009
Total	3,132,387	2,514,912	903,186	6,550,485

Table 2.2: Average input and output levels by year and ownership type (Standard deviation in parentheses)

(a) Public

Year	X1	X2	X3	X4	Y1	Y2	Y3	Y4	Y5
2000	110.18	260.47	283.96	251.18	831.99	320.34	859.57	3,061.86	5,705.47
	(363.51)	(525.64)	(790.62)	(723.68)	(4,619.60)	(307.44)	(6,066.48)	(6,894.97)	(12,730.93)
2001	123.94	292.41	215.90	248.82	931.45	301.22	882.19	3,277.69	5,658.58
	(364.49)	(550.88)	(812.05)	(589.02)	(4,679.89)	(284.89)	(6,297.75)	(7,378.87)	(13,706.07)
2002	129.38	290.06	209.38	234.92	1,044.07	276.05	910.75	3,416.62	5,696.95
	(345.76)	(609.48)	(791.27)	(559.86)	(4,795.72)	(296.18)	(5,368.57)	(7,154.56)	(14,199.20)
2003	134.48	293.48	248.42	215.75	1,045.99	249.30	946.01	3,383.72	5,706.03
	(317.14)	(556.32)	(701.58)	(502.01)	(4,679.07)	(275.42)	(5,142.27)	(6,964.78)	(14,781.81)
2004	128.53	281.65	228.47	219.86	1,179.58	235.20	960.47	3,607.16	5,882.19
	(309.94)	(593.69)	(745.73)	(509.28)	(5,001.92)	(280.82)	(5,022.41)	(7,205.18)	(15,466.18)
2005	141.76	316.93	305.60	233.38	1,377.72	261.45	1,076.66	3,726.86	6,294.96
	(306.74)	(465.72)	(976.94)	(490.17)	(4,759.24)	(309.55)	(4,960.56)	(7,552.57)	(16,476.76)

(b) NFP

Year	X1	X2	X3	X4	Y1	Y2	Y3	Y4	Y5
2000	239.56	446.00	528.19	524.31	2,309.48	251.37	3,835.24	6,199.18	11,237.66
	(363.51)	(525.64)	(790.62)	(723.68)	(4,619.60)	(307.44)	(6,066.48)	(6,894.97)	(12,730.93)
2001	246.06	465.56	543.06	478.06	2,435.05	238.47	4,133.73	6,601.94	11,917.19
	(364.49)	(550.88)	(812.05)	(589.02)	(4,679.89)	(284.89)	(6,297.75)	(7,378.87)	(13,706.07)
2002	244.76	477.71	525.65	452.53	2,560.05	264.87	4,032.31	6,970.77	12,161.03
	(345.76)	(609.48)	(791.27)	(559.86)	(4,795.72)	(296.18)	(5,368.57)	(7,154.56)	(14,199.20)
2003	238.41	462.18	493.18	432.41	2,693.21	255.55	4,108.43	7,222.96	12,483.86
	(317.14)	(556.32)	(701.58)	(502.01)	(4,679.07)	(275.42)	(5,142.27)	(6,964.78)	(14,781.81)
2004	247.71	473.35	512.12	430.94	3,077.25	262.53	4,177.61	7,645.00	12,941.68
	(309.94)	(593.69)	(745.73)	(509.28)	(5,001.92)	(280.82)	(5,022.41)	(7,205.18)	(15,466.18)
2005	231.94	359.44	562.28	408.33	2,917.56	256.40	4,014.03	7,895.34	13,130.73
	(306.74)	(465.72)	(976.94)	(490.17)	(4,759.24)	(309.55)	(4,960.56)	(7,552.57)	(16,476.76)

(c) Private

Year	X1	X2	X3	X4	Y1	Y2	Y3	Y4	Y5
2000	28.98	35.97	47.63	90.32	71.18	47.75	146.94	1,608.93	1,449.47
	(24.66)	(35.72)	(39.78)	(57.03)	(146.70)	(111.11)	(161.95)	(2,322.44)	(1,167.74)
2001	31.37	37.87	48.87	88.82	84.81	42.57	164.57	1,818.65	1,532.32
	(28.26)	(37.74)	(41.13)	(60.32)	(190.20)	(94.26)	(178.16)	(2,565.21)	(1,162.38)
2002	30.50	38.00	52.82	89.39	98.44	44.00	177.96	1,759.58	1,615.98
	(25.66)	(37.23)	(41.78)	(58.75)	(191.00)	(94.20)	(177.53)	(1,694.00)	(1,226.36)
2003	28.13	34.00	50.38	86.08	104.45	41.06	190.00	1,949.14	1,651.48
	(25.42)	(34.85)	(40.69)	(59.26)	(220.28)	(84.06)	(188.48)	(1,873.98)	(1,170.07)
2004	31.10	37.49	49.92	86.36	141.22	51.12	205.32	2,200.36	1,650.19
	(29.71)	(37.53)	(42.69)	(61.70)	(317.65)	(85.64)	(226.94)	(2,122.48)	(1,191.93)
2005	40.22	47.81	57.33	84.28	312.51	82.91	220.61	2,682.13	1,856.20
	(30.37)	(54.06)	(43.48)	(60.94)	(915.72)	(134.86)	(240.61)	(2,959.23)	(1,185.41)

Notes: X_1: Physicians, X_2: Nurses, X_3: Other staff, X_4: Beds
Y_1: Complex Surgery, Y_2: ER treatments, Y_3: HIV and tumors, Y_4: General surgery Y_5: General medicine

Table 2.3: LR tests on functional form restrictions (H_1 : translog model with "full" heteroscedasticity and mean inefficiency)

(a) Output distance function - $\ln \mathcal{L}(H_1)$= -119.6972

Null hypothesis	Log-likelihood	λ	Decision
$H_0 : \mu_i = 0$	-197.3668	155.34	Reject
$H_0 : \mu_i = \mathbf{w}_i = \mathbf{t}_i = 0$	-267.7312	296.07	Reject
$H_0 : \mathbf{w}_i = \mathbf{t}_i = 0$	-153.1636	66.93	Reject
$H_0 : \mathbf{q}_i = 0$	-195.3250	151.26	Reject

(b) Input distance function - $\ln \mathcal{L}(H_1)$= 133.1165

Null hypothesis	Log-likelihood	λ	Decision
$H_0 : \mu_i = 0$	80.0164	106.20	Reject
$H_0 : \mu_i = \mathbf{w}_i = \mathbf{t}_i = 0$	-85.0366	436.61	Reject
$H_0 : \mathbf{w}_i = 0$	78.6063	109.02	Reject
$H_0 : \mathbf{q}_i = 0$	84.9903	96.25	Reject

Table 2.4: Scale and output/input elasticities evaluated at the average values for the entire sample

	Output distance			**Input distance**	
	Est.	St.Err.		Est.	St.Err.
$\epsilon_{\mathbb{Y},\mathbb{X}}$	1.257 **	0.257	$\epsilon_{\mathbb{X},\mathbb{Y}}$	0.703 ***	0.029
$\epsilon_{\mathbb{Y},X_1}$	0.173 *	0.101	$\epsilon_{\mathbb{X},X_1^*}$	0.071	0.047
$\epsilon_{\mathbb{Y},X_2}$	0.646 ***	0.181	$\epsilon_{\mathbb{X},X_2^*}$	-0.157 **	0.062
$\epsilon_{\mathbb{Y},X_3}$	-0.074	0.089	$\epsilon_{\mathbb{X},X_3^*}$	0.112 ***	0.035
$\epsilon_{\mathbb{Y},X_4}$	0.512 ***	0.153	$\epsilon_{\mathbb{X},X_4^*}$	0.974 ***	0.057
$\epsilon_{\mathbb{Y},Y_1^*}$	0.007	0.027	$\epsilon_{\mathbb{X},Y_1}$	0.013	0.012
$\epsilon_{\mathbb{Y},Y_2^*}$	0.089 ***	0.034	$\epsilon_{\mathbb{X},Y_2}$	-0.007	0.020
$\epsilon_{\mathbb{Y},Y_3^*}$	0.177 ***	0.055	$\epsilon_{\mathbb{X},Y_3}$	0.017	0.017
$\epsilon_{\mathbb{Y},Y_4^*}$	0.190 ***	0.056	$\epsilon_{\mathbb{X},Y_4}$	0.248 ***	0.029
$\epsilon_{\mathbb{Y},Y_5^*}$	0.537 ***	0.059	$\epsilon_{\mathbb{X},Y_5}$	0.432 ***	0.028

Notes: X_1: Physicians, X_2: Nurses, X_3: Other staff, X_4: Beds
Y_1: Complex Surgery, Y_2: ER treatments, Y_3: HIV and tumors,
Y_4: General surgery Y_5: General medicine
Significance levels : $*$: 10% $**$: 5% $***$: 1%

Table 2.5: Shifting factors parameters of the stochastic frontier models and ancillary equations - Pooled Cross Section. The dependent variable in the Output Distance model is the inverse of complex surgery weights. In the Input Distance model the dependent is the inverse of the number of beds.

	Output Distance	Input Distance
Production frontier		
Private	0.008	0.178 **
Not-for-profit	-0.204 ***	0.108 *
Year 2001	-0.018	0.056 ***
Year 2002	-0.061	0.101 ***
Year 2003	-0.101 **	0.162 ***
Year 2004	-0.117 **	0.167 ***
Year 2005	-0.144 ***	0.206 ***
Viterbo	-0.223 **	0.196 ***
Latina	-0.082 ***	0.020
Rieti	-0.211	0.188 ***
Frosinone	-0.158 **	0.135 **
Rome-asl	-0.057	0.011
Rome-self	0.021	-0.082
Intercept	-0.154 *	0.407 ***
Mean of **u**		
Weighted patients	-	-0.032
Beds	-2.356 ***	-
Gini	-9.022 *	-2.229 ***
Nurses/Bed	-12.923 **	-0.404 ***
Age	-	0.006 ***
Intercept	9.442 **	1.704 ***
Variance of **u**		
Beds	-0.069	-
Intercept	0.386	-5.321 ***
Variance of **v**		
Weighted patients	-	-0.871 ***
Beds	-1.087 ***	-
Intercept	-3.491 ***	-3.135 ***
N. obs.	625	625
Likelihood	119.70	133.12

Notes: Significance level based on clustered standard errors. Technology parameters omitted. Complete table available upon request

Significance levels : $*$: 10% $**$: 5% $***$: 1%

Table 2.6: Second-order effects of the input distance model

	Complex Surgery	ER treatments	HIV and tumors	General Surgery	General Medicine
Complex Surgery	-0.012				
ER treatments	0.010	-0.001			
HIV and tumors	-0.006	0.010	-0.082***		
General Surgery	-0.018**	-0.032***	0.034***	-0.032**	
General Medicine	0.010	0.025	0.061***	0.010	-0.123***

Table 2.7: Transition matrix: quintile of technical efficiency (TE) from 2000 to 2005.

(a) Output distance model

Quintile of TE at 2000	**Quintile of TE at 2005**					
	1	2	3	4	5	.
1	11	7	0	0	0	3
	52.38	33.33	0.00	0.00	0.00	14.29
2	6	6	3	4	1	1
	28.57	28.57	14.29	19.05	4.76	4.76
3	1	1	8	4	2	5
	4.76	4.76	38.10	19.05	9.52	23.81
4	0	1	4	8	7	1
	0.00	4.76	19.05	38.10	33.33	4.76
5	0	3	4	4	8	2
	0.00	14.29	19.05	19.05	38.10	9.52

(b) Input distance model

Quintile of TE at 2000	**Quintile of TE at 2005**					
	1	2	3	4	5	.
1	9	9	1	1	0	1
	42.86	42.86	4.76	4.76	0.00	4.76
2	10	3	3	3	1	1
	47.62	14.29	14.29	14.29	4.76	4.76
3	1	5	7	5	0	3
	4.76	23.81	33.33	23.81	0.00	14.29
4	0	2	6	6	3	4
	0.00	9.52	28.57	28.57	14.29	19.05
5	0	0	2	4	12	3
	0.00	0.00	9.52	19.05	57.14	14.29

Notes: The last column represents those observations that were part of the sample in 2000 but missing in 2005.

2.8 Figures

Figure 2.1: Trends in technical efficiency (2000-2005)

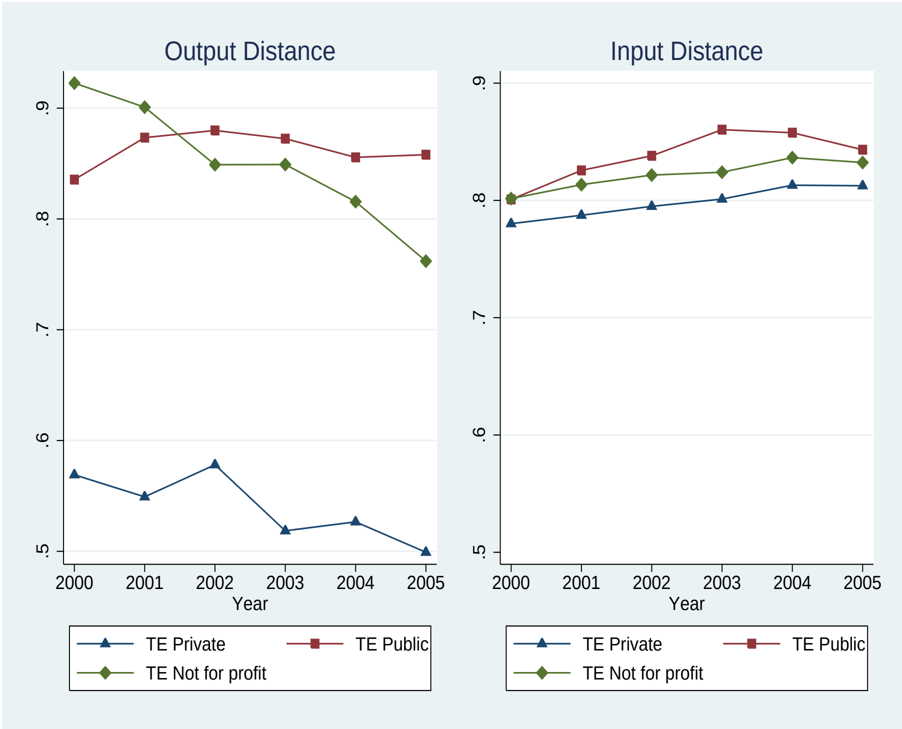


Figure 2.2: Transitions in technical efficiency (2000-2005)

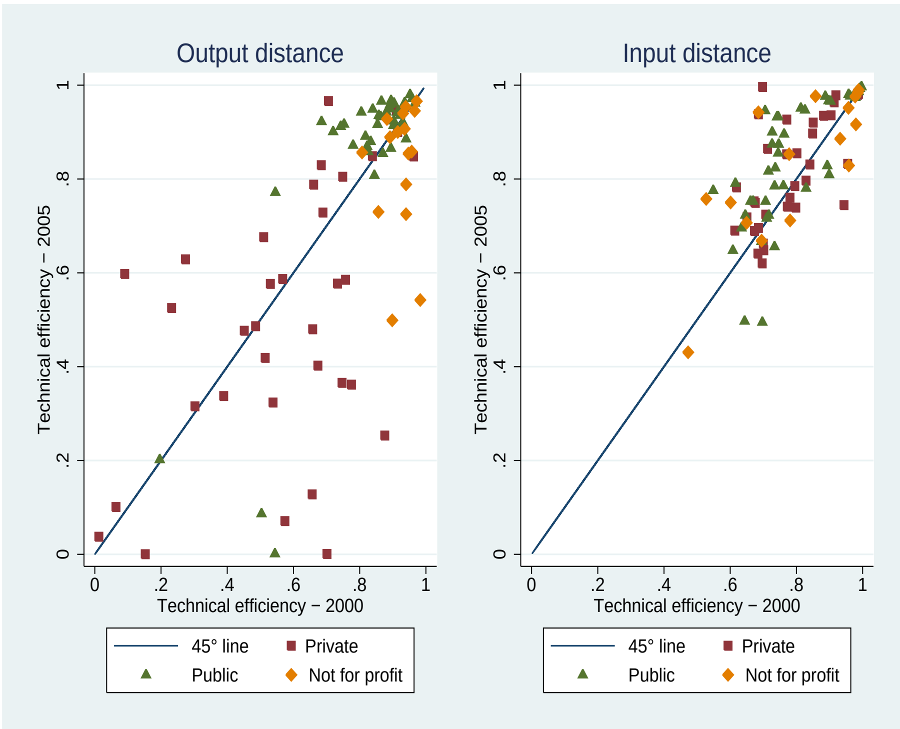
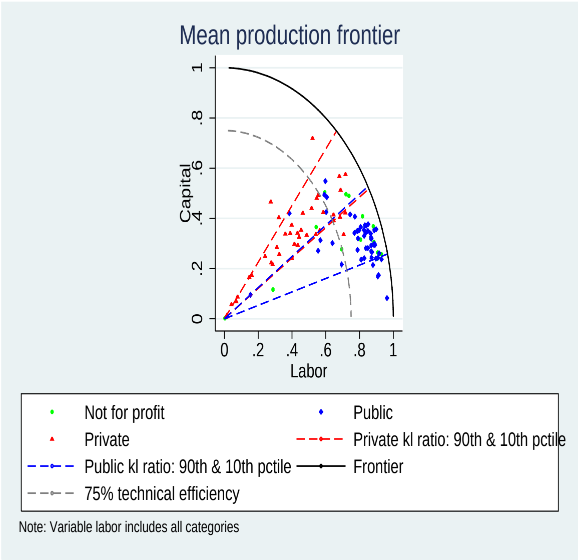
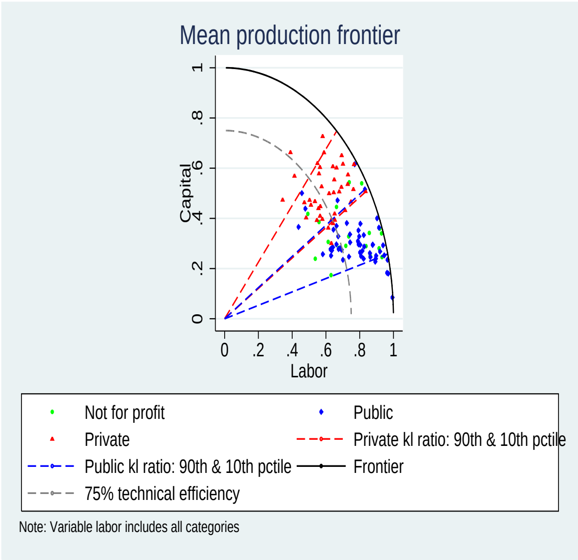


Figure 2.3: Capital-labor ratio, production frontier, and Technical Efficiency



(a) Output Distance



(b) Input Distance

Within households effects of expanding rural nonfarm sector in a developing country. [22]

Abstract

This article explores the effects within households of an expanding rural nonfarm (RNF) sector in Ghana. We ask whether the growing RNF sector allows for economies of diversification within farms and how it affects household input demands. We explore the intrahousehold linkages between agricultural and RNF activities, first assuming perfectly competitive input and output markets and then with market failures, in particular missing labor and credit markets. We then measure these linkages using a household level input distance function, finding high levels of inefficiency in Ghanaian farms. Also, there are cost-complementarities between the RNF sector and the agricultural sector, particularly with food crops in which the poorest tend to specialize. The expansion of the RNF sector increases demand for most inputs including agricultural land.

[22] This paper is based on "Linkages between the farm and nonfarm sectors at the household level in rural Ghana: a consistent stochastic distance function approach" with Gustavo Anríquez, published in *Agricultural Economics*, 41:51-66 (2010). The authors thank participants at the FAO conference on Household-Level Linkages between Farm and Nonfarm Rural Activities and an anonymous referee for comments that have helped improve this work. Remaining errors and omissions are our exclusive responsibility.

3.1 Introduction

In the modern literature, Kuznets (1957) first formally documented the contraction of the agriculture sector relative to the rest of the economy that occurs as countries become wealthier. This is now an accepted feature of national economic development. A similar and related process can be observed in rural economic development. As countries grow, agriculture becomes less important in their rural economies, and the rural nonfarm (RNF) sector of manufactures and services grows more rapidly than farm output. This transformation of the rural world should also be considered a feature of economic development, and has been formally documented by Reardon et al. (1998) and Davis et al. (2007), among others. The first macroeconomic transformation has important implications for the role of agriculture as an engine of growth and development, and has been amply studied in the literature for many years. The transformation in the rural economy also has sectoral implications, which have been less extensively studied, mainly using Social Accounting Matrices (SAM) and Computed General Equilibrium Models (see for example Haggblade et al. (1989); Vogel (1994); and references contained therein). However, the growth of the RNF economy also has important microeconomic consequences for the economic behavior of rural households, but these have been largely ignored in the literature.

This study examines the linkages between the agriculture and nonfarm sectors at the microeconomic level, within the household. Using a case study from Ghana, we seek to determine whether there are productive linkages within the household, or a household-level multiplier, which would make diversification beneficial for farms. The existence of such linkages would warrant a policy of promoting the RNF sector wherever barriers to entry (such as education, or access to credit) or other market failures hinder its development.

The sectoral relationship between agriculture and the rest of the economy has been a main concern since the early days of development economics. The first development economists painted a grim picture of the agriculture sector. Lewis (1954), for example, observing that agricultural labor generated only a negligible or negative marginal product, saw the sector as merely a source of labor for urban and industrial development, without noting any general equilibrium effect among sectors in the demand for unskilled labor. Hirschman (1958) explored the input-output linkages between agriculture and the rest of the economy. He argued that agriculture's backward linkages, that is, the sector's capacity to "pull" the rest of the economy by increasing intermediate input demand as it expands, were very low, so the sector was therefore not worth promoting. This became the common perception, and agricultural economists seeking to promote the sector started to focus on consumption linkages. Authors such as Haggblade et al. (1989) began to show that the agriculture sector has a very high household demand multiplier. This means that the increased demand caused by higher household income from agriculture has a very high multiplier effect across the rest of the economy, particularly in closed economies; many developing rural economies are effectively closed owing to high transaction costs. Agricultural economists also focused on forward linkages, or agriculture as an input for downstream activities such as food processing or hospitality services (see for example Valdés and Foster (2003).

The conclusion drawn from this macrolevel sectoral view is that productive linkages are important. For example, Blunch and Verner (2006) use time-series sectoral growth figures from agriculture, industry and services in three African nations to show that there are two- way spillovers between agricultural and industrial growth in Zimbabwe, Côte d'Ivoire and Ghana. A multiplier analysis using input-output matrices will show that both forward and backward linkages are more important at early stages of development. When household accounts are added to this multiplier analysis, as with a SAM, demand multipliers are found to be high at early stages of development (see Vogel (1994)). There are many nuances in these sectoral linkages: some agricultural activities have high forward linkages, for example through marketing of processed food, while others have inherently less linkage potential (see for example the case studies in Davis et al. (2002)).

3.1.1 The Ghanaian rural nonfarm sector

During the 1990s the Ghanaian economy experienced positive per capita growth and a reduction of the national poverty rate by roughly a quarter, from 51.7% in 1991/1992 to 39.5% in 1998/1999 (see Table 3.1). In the rural economy, national account figures indicate very little growth in agricultural value added per capita but large gains in household expenditure (and consequently in poverty reduction), along with considerable growth of per capita agricultural production reported by Food and Agriculture Organization (FAO). This combination of what appears to be slow agricultural growth and fast rural poverty reduction is partly explained by a rapid expansion of the RNF sector. For example, Table 3.1 shows that nonfarm self-employed income in rural Ghana grew from 11.9% of total household income in 1991/1992 to 23.6% in 1998/1999. These big changes within rural households are likely to have an important impact on farm production.

In this study we ask whether an expansion of nonfarm output hinders farm output growth by competing for scarce household inputs, or promotes it through complementarities and economies of diversification. Further we explore the ways in which input demand might change, for example if RNF output helps households pay for farm input purchases.

The following two sections present the theoretical framework: a microeconomic analysis of household-level linkages among sectors, and the input distance function used in the empirical study. The fourth section discusses the econometric and empirical issues associated with estimating a stochastic distance function. Results of the empirical analysis are presented and discussed in the fifth section, which is followed by concluding remarks.

3.2 Linkages between farm and nonfarm activity in a household model

With perfectly competitive markets for all inputs and all outputs, price-taking households would make separate decisions regarding production and consumption, first choosing inputs and outputs to maximize profits given their production possibilities, and then choosing consumption to maximize welfare given their income level. However, market failures lead production and consumption decisions to be taken jointly, including choices between farm and nonfarm products. This section seeks to clarify these relationships in a household model.

Households are assumed to maximize a quasi-concave utility function: $U(\mathbf{c}, T - L^s$. Well-being depends on the consumption vector c and on leisure time, which is total available time T minus labor supply L^s. Maximization of U is constrained by income

$$\sum_j p_j c_j + w(T - L^s) \leq wT + p_0 Q_F + Q_N - wL^D - \sum_i w_i x_i + E \tag{3.1}$$

In this budget constraint, total consumption is valued at market prices p_j and time is valued at its opportunity cost or market wage. The price of nonfarm output is used as the numeraire. Total consumption cannot be higher than full income, which is the value of available time plus exogenous income E, plus the rents of producing farm output Q_F and nonfarm output Q_N. Outputs are measured as consumption quantities in the **c** vector. Rents are net of the costs of inputs, purchased variable inputs x_i with unit cost w_i, and labor used L_D. The labor supplied L_s and labor employed L_D need not be equal; if the former is larger, household labor is hired out to work elsewhere, if it is smaller, the household hires in external labor. Household welfare is also constrained by technology, represented by an implicit production function as $G\left(Q_F, Q_N; L^D, \mathbf{x}; K\right) = 0$, where K represents medium term fixed assets and household characteristics such as land, capital and human capital. Further constraints are imposed by nonnegativity of all quantities. To focus on production choices, we can express the model as minimizing production costs, in which case the budget and technical constraints can be merged into one

$$\sum_j p_j c_j + w(T - L) \leq wT + p_0 Q_F + Q_N - C\left(Q_F, Q_N; \mathbf{w}; K\right) + E \tag{3.2}$$

where the function $C()$ is the cost function defined as

$$C\left(Q_F, Q_N; \mathbf{w}; K\right) \equiv \min_{L, \mathbf{x}} \left\{ wL^D + \sum_i w_i x_i | G\left(Q_F, Q_N; L, \mathbf{c}; K\right) = 0 \right\} \tag{3.3}$$

Production choices would be separable from consumption if households were price takers in perfectly competitive input and output markets (see Singh et al. (1986) for details). In those conditions, the highest utility would be obtained when production responds to market prices, whether or not some part of production is actually consumed on the farm

$$\max_{Q_F, Q_N} wT + p_0 Q_F + Q_N - C\left(Q_F, Q_N; \mathbf{w}; K\right) + E \tag{3.4}$$

The first-order conditions for this income maximization problem are $p_0 = C_{Q_F}()$, and $1 = C_{Q_N}()$. Differentiating the first condition with respect to the output vector (and not to prices, as the household is a price taker), and rearranging, results in

$$\frac{\partial Q_F}{\partial Q_N} = -\frac{C_{Q_N, Q_F}}{C_{Q_F, Q_F}} \tag{3.5}$$

This means that farm output can actually increase after an exogenous increase in nonfarm output if there are cost complementarities, i.e., $C_{Q_N, Q_F} < 0$.[23]

3.2.1 Cost complementarities and economies of scope

The concepts of cost complementarities and economies of scope are related, but are not the same. Economies of scope occur when it is cheaper to produce goods jointly than to produce them separately

[23] It is implicitly assumed that C_{Q_F, Q_F} is positive. In a strictly technological sense, this derivative could be negative, but the economic area of this function - where rents are positive - is defined by increasing marginal costs, i.e., $C_{Q_F, Q_F} \geq 0$.

$$ES = \frac{C\left(Q_N = 0, Q_F; w, \mathbf{q}; K\right) + C\left(Q_N, Q_F = 0; w, \mathbf{q}; K\right) - C\left(Q_N, Q_F; w\mathbf{q}; K\right)}{C\left(Q_F, Q_N; w, \mathbf{q}; K\right)}$$

There are two sources of economies of scope: savings in fixed costs, when the fixed costs of joint production are lower than the separate fixed costs; and cost complementarities, caused by the shared use of variable production inputs and other cost saving mechanisms implicit in joint production. Note that even when these sources act in opposite directions, economies of scope are observed, cf. Gorman (1985). If a household can produce positive amounts of both outputs at market prices, and economies of scope are present, that household would clearly be better off if it produces both outputs.

This study hypothesizes that economies of scope are likely to be important for even poor rural households, as explained in the following:

- Distribution of fixed costs: This type of scope economy is not restricted to high-value fixed costs, such as expensive machinery and equipment. The important issue is not the nominal value of the fixed costs, but their value relative to variable costs. For poor households, housing infrastructure is usually the largest fixed asset, and is necessary for farm and nonfarm operations.

- Distribution of variable inputs used in both operations: This type of complementarity exists in even the poorest household, as food is an input for labor productivity in both sectors, and labor effort can be shared across outputs. For example, one set of marketing efforts can be made to market both types of goods.

- Cost complementarities caused by externalities: For example, a nonfarm activity can create capacities and skills that help improve the household's management of agricultural operations (e.g., bookkeeping or budget management).

- Inputs for the other operation are produced at below market prices: This type of cost complementarity can arise when a farm input or by-product is used in the nonfarm operation, and is produced at a shadow price below the market price.

3.2.2 The household model with missing labor markets

In Ghana's rural economy, it seems very unlikely that households actually face a given wage rate at which labor can be both bought and sold. In a study of 15 developing countries, Davis et al.

(2007) found that wage income (agricultural plus nonfarm wages) as a share of total household income was only from 9% to 11% in rural Ghana, suggesting that the extent of paid labor markets is very limited. In the absence of a labor market, the implicit household shadow wage rate has to be calculated from the equilibrium between the disutility of working and the productivity of effort in generating income, and the households labor effort, income and consumption all depend on both their utility function and their production technology.

When labor markets are missing, assuming that nonnegativity constraints are not binding, household equilibrium can be defined with two equations

$$e(\mathbf{p}, w; \overline{U}) = wT + pQ_F + Q_N - C(Q_F, Q_N; w, \mathbf{q}; K) + E \tag{3.6}$$

$$T - e_w = C_w \tag{3.7}$$

Here the expenditure function $e()$ is used to value consumption, defined as

$$e(\mathbf{p}, w; \overline{U}) = \min_{\mathbf{c}, T-L^s} \left\{ \sum_j p_j c_j + w(T - L^s) | U(\mathbf{c}, T - L^s \geq \overline{U} \right\}$$

Equation (3.7) defines intrahousehold labor market equilibrium, which hinges on the shadow wage rate, w^*, at which the supply of labor (i.e., the residual of the demand for leisure) is equal to the labor demand schedule from the productive side of the household. As there is no external labor to be hired, and no external demand for labor, the implicit shadow wage rate is determined within the household. The amount of labor employed in the household can be obtained by evaluating either side of Eq. (3.7) at the shadow wage rate that solves (3.6) and (3.7) jointly. Totally differentiating (3.7) and rearranging terms we get the effect of increasing farm output on the shadow wage rate

$$\frac{\partial w^*}{\partial Q_F} = \frac{-C_{w,Q_F}}{(e_{w,w} + C_{w,w})} = \frac{-\frac{\partial L^D}{\partial Q_F}}{\left(\frac{\partial (T-L^s)}{\partial w^*} + \frac{\partial L^D}{\partial w^*}\right)} > 0 \tag{3.8}$$

The denominator of (3.8) is unambiguously negative because both the expenditure and the cost functions are concave in prices - as a result of only the quasi-concavity of the welfare function and the convexity of technology - while the numerator is negative when labor is a normal input (a safe assumption). This means that an exogenous increase in farm (or nonfarm) output increases the marginal product of labor, which is the shadow price w^*. The production first-order conditions can now be totally differentiated, with w now variable

$$\frac{\partial Q_N}{\partial Q_F} = -\frac{C_{Q_N,Q_F}}{C_{Q_N,Q_N}} - \frac{C_{Q_N,w}}{C_{Q_N,Q_N}} \cdot \frac{dw^*}{dQ_F} - \frac{C_{Q_N,Q_F}}{C_{Q_N,Q_N}} - \frac{\partial L^D/\partial Q_N}{C_{Q_N,Q_N}} \cdot \frac{dw^*}{dQ_F} \tag{3.9}$$

Therefore, in the absence of a working labor market, the production linkage between outputs is lower. The cost complementarity effect is reduced because an exogenous increase in farm output generates an increase in the marginal productivity of labor through an increase in the shadow wage rate, which reduces the demand for labor in nonfarm production. In addition, the pure labor effect of expanding the output in one sector is negative for the output of the other.

3.2.3 The household model with cash constraints

The nonfarm economy is often seen as an alternative source of cash or working capital for agriculture, when farm credit markets are not working efficiently (see for example Reardon et al. (2007)). To isolate such a cash constraint effect in an otherwise separable household model, the household maximizes income as described in Eq. (3.4) but is subject to

$$Q_N > \overline{Q}_N \tag{3.10}$$

where $\overline{Q}_N$ is the minimum level of farm output to guarantee cash for food and inputs. The first order conditions are simply $p_0 = C_{Q_F}()$ and

$$1 + \mu = C_{Q_N} \tag{3.11}$$

where μ is the lagrangian multiplier associated with the minimum nonfarm output constraint. In this case dQ_N/dQ_F cannot be calculated, because the household is at a corner solution, but several conclusions can be derived from (3.11).

First, the household is producing more Q_N than would otherwise be optimal. Relative to the unconstrained optimum, the nonfarm sector is producing at a loss with its marginal costs $(1 + \mu)$ exceeding marginal revenues. When there are cost complementarities, an exogenous increase in farm output would reduce these efficiency losses. From (3.11) it can be shown that

$$\frac{\partial \mu}{\partial Q_F} = C_{Q_N, Q_F} < 0$$

Thus, when there are cost complementarities and an exogenous expansion of farm output, the income effect will be larger than dQ_F , even in cash-constrained households.

One potentially testable implication from this model of nonfarm activity and credit constraints is that variable inputs, including labor, would produce a lower value of marginal product in the nonfarm than in the farm sector. Another testable implication is that the household does not operate at the optimal point of its production possibility frontier

$$p_0 = \frac{C_{Q_F}}{C_{Q_N}} > \frac{p_0}{(1+\mu)} \tag{3.12}$$

3.3 Empirical estimation using an input Shepherd's distance function

For an empirical assessment of the technological linkages between farm and nonfarm production, we estimate a distance function defined as

$$D(\mathbf{x}, \mathbf{Q}) \equiv \sup_{\lambda} \left\{ \lambda^{-1} \mathbf{x} | (\mathbf{x}, \mathbf{Q}) \in \ T) \right\} = \inf_{\lambda} \left\{ \lambda^{-1} \mathbf{x} | \mathbf{x} \in L(\mathbf{Q}) \right\} \tag{3.13}$$

where T represents the technology (the technologically feasible set), $L(\mathbf{Q})$ represents the input requirement set (all the input combinations that can produce the output bundle $\mathbf{Q}$), and $\mathbf{x}$ represents an inputs vector. The function describes the largest radial contraction of inputs that leaves the production of an output bundle $\mathbf{Q}$ technologically feasible. This radial contraction is special in that it contracts all inputs by the same proportion. Fig. 3.1 provides an example with two inputs: the input set A produces the output bundle $\mathbf{Q}$, but could be proportionally contracted to point B and still produce the same output bundle. In this case the value of the distance function is OA/OB. The figure also shows how the input distance function has to be greater than or equal to one, and have strict equality when TE is achieved at the isoquant. As the input distance function fully represents the technology there is a direct correspondence $(\mathbf{x}, \mathbf{Q}) \in T \Longleftrightarrow D(\mathbf{x}, \mathbf{Q}) \geq 1$.

A distance function is estimated because there is a direct relationship among the cost minimization hypothesis, the cost function and the input distance function, so all the cost function properties discussed in the previous section are easily obtained from the distance function. The input distance function is preferred over the cost function because its estimation does not require reliable price information. In rural Ghana, two of the most important inputs of agricultural production, land and labor, have extremely underdeveloped markets. This means that each household has its own shadow labor price, which is unknown, and land is rarely traded, which makes it very difficult even for farmers to obtain accurate land values and prices. Even food crops are not always traded, so the market price is not always relevant to the shadow price in household production.

The inputs and output bundles that are technically feasible are represented by $D(\mathbf{Q}, \mathbf{x}) \geq 1$, so the cost function can be expressed as

$$C(\mathbf{w}, \mathbf{Q}) = \min_{\mathbf{x}} \left\{ \mathbf{w}'\mathbf{x} | D(\mathbf{x}, \mathbf{Q}) \geq 1 \right\} \tag{3.14}$$

Applying the envelope theorem to the maximization problem associated with (3.14) leads to

$$\frac{\partial C(\mathbf{w}, \mathbf{Q})}{\partial Q_i} = -\eta \cdot \frac{\partial D(\mathbf{x}, \mathbf{Q})}{\partial Q_i}$$

and

$$\frac{\partial^2 C(\mathbf{w}, \mathbf{Q})}{\partial Q_i \partial Q_i} = -\eta \cdot \frac{\partial^2 D(\mathbf{x}, \mathbf{Q})}{\partial Q_i \partial Q_i} \tag{3.15}$$

where $\eta = \mathbf{w}'\mathbf{x} = C(\mathbf{w}, \mathbf{Q})$.[24] Therefore, the marginal cost is equal to the partial derivative of the input distance function for the same output, but with the opposite sign and multiplied by the value, which is the total cost.

Another important derivative property of the distance function is the returns to scale measure, which in an input distance function is given by $\epsilon = [-\sum_j \partial \ln D(\mathbf{x}, \mathbf{Q}) / \partial \ln \mathbf{Q}_j]^{-1}$. The technology exhibits decreasing (increasing) returns to scale when $\epsilon < 1$ ($\epsilon > 1$).

3.4 Empirical implementation using a consistent stochastic distance function

Most empirical estimations of distance function exploit the linear homogeneity of the function to estimate a Translog approximation. First, using the linear homogeneity property, the distance function is reexpressed as: $x_0 \cdot D(\mathbf{x}/x_0, \mathbf{Q}) = \lambda$, after dividing and multiplying by any particular input. Applying logarithms, rearranging and adding an unbiased random noise term (e^v) results in

[24]See Färe and Primont (1995): chapters 2 and 3 for details.

$$-\ln x_0 = \ln D(\mathbf{x}/x_0, \mathbf{Q}) - \ln\lambda + v \tag{3.16}$$

where $\ln\lambda$ is u, the one-sided error term identified in the stochastic frontier literature, and $\ln D()$ is approximated by the translog functional form. Expression (3.16) can be estimated with stochastic frontier methods (see Kumbhakar and Lovell, 2000) that maximize the joint likelihood of the one-sided error (assumed to be distributed half-normal, truncated normal, exponential or gamma) and a normally distributed random noise v.

This study cannot apply this approach because the different outputs contain zero as a value, particularly the nonfarm sector output for many rural households. Alternatives include replacing zeroes with arbitrarily small units, or replacing the logs with arbitrarily large negative numbers, but these arbitrary solutions would affect the properties of the estimated technology. A functional form that does not apply a log transformation has therefore to be used. In this case

$$\frac{1}{x_0} = D(\mathbf{x}/x_0, \mathbf{Q}) - u + v \tag{3.17}$$

could be estimated. However, the "true" model as defined by 3.13 is $\lambda/x_0 = D(\mathbf{x}/x_0, \mathbf{Q})$, which means that the error term in this case is

$$u = (\lambda - 1)/x_0 \tag{3.18}$$

Equation (3.18) shows that, as expected, the one-sided error term is positive as the value of the distance function $\lambda \geq 1$. However, (3.17) violates a key assumption of the stochastic frontier model and the classical linear regression model in general: the one-sided error u is not independent of the regressors. In particular, with respect to the input regressors, $E[(x_i/x_0)\cdot(u)] = E[(x_i/x_0)\cdot(\lambda-1)/x_0] \neq 0$, which means that the estimated coefficients are inconsistent in proportion to the inefficiency $(\lambda - 1)$ in the decision-making units.

The distance function can therefore be estimated from

$$\frac{\hat{\lambda}}{x_0} = D\left(\frac{\mathbf{x}}{x_0}, \mathbf{Q}\right) + v \tag{3.19}$$

which follows directly from (3.13) after normalizing by an input and applying the linear homogeneity property, with v as the mean zero random noise. $\hat{\lambda}$ is estimated by calculating the Farrell input-oriented TE (Farrell, 1957), using data envelopment analysis (DEA) techniques.[25] The original Charnes et al. (1978) model is used, which is equivalent to estimating input-oriented TE assuming constant returns to scale (CRS).

The method for estimating an input distance function described in (3.19) is not ideal in that it does not allow the direct econometric identification of and is computationally intensive. On the other hand, the benefits of this method are that it does not rely on an assumption about the distribution of technical inefficiency and it is consistent. Stochastic frontier methods are not ideal either, because λ is econometrically identified indirectly and only after making a distributional assumption that may or may not hold. As shown below, when the inefficiency λ is large, the estimated technology parameters become unreliable if the wrong distribution has been assumed.

3.4.1 Endogeneity of regressors

Under cost minimization, outputs can be taken as exogenous as seen in (3.14), but inputs are endogenously chosen by producers. Early attempts to estimate a stochastic distance function used instrumental variable (IV) methods to overcome endogeneity, but Coelli (2000) showed that with cost minimization the distance function estimated as (3.16) provides a consistent estimation of the underlying technology even under allocative inefficiency. This important result follows from the estimated distance function being a function of input ratios, not inputs, and on these being uncorrelated with the TE residual. Consistency of the estimates is generalized further in Coelli et al. (2007), where different types of multiplicative errors in observed x'sfs are present, such as technical inefficiency or measurement error. In both cases, consistency relies on the definition of the distance function; if the technically efficient level $x_1^t \equiv \frac{x_1}{\lambda}$ is defined as in (3.13), the ratios of observed inputs $\frac{x_1}{x_2} = \frac{x_1^t}{x_2^t}$ are also technically efficient, by definition.

There is a cost, however, to the input normalization of the distance function. Although in theory it does not matter which input is used to normalize the function, in practice it matters and results vary. It has been shown, for example, in the context of cost function estimation that the chosen normalizing input (when linear homogeneity in prices of the cost function is imposed) significantly affects the estimated technology. One alternative is to normalize by the Euclidian norm of the input vector $||\mathbf{x}||$ (Kumbhakar and Lovell (2000)). This eliminates the arbitrariness of the normalizing

[25] Färe et al. (1994) is a good manual for DEA methods

input choice, but it is not clear that it allows consistent estimation of the underlying technology parameters. To eliminate this arbitrariness, and exploit the full variability of the data set, the distance function can be estimated in a system of equations

$$\begin{aligned}
\frac{\hat{\lambda}}{x_0} &= D\left(\frac{\mathbf{x}}{x_0}, \mathbf{Q}\right) + v_0 \\
&\vdots \\
\frac{\hat{\lambda}}{x_n} &= D\left(\frac{\mathbf{x}}{x_n}, \mathbf{Q}\right) + v_n
\end{aligned} \tag{3.20}$$

in which all parameters of the linear approximation of the distance function must be equal across equations, and the crossequation error correlation is exploited in a maximum likelihood system of unrelated regressions (ML SUR).

This study approximates the distance function (with four outputs and four inputs as described in the following) with the following flexible functional form, which is a Generalized Leontief function

$$\begin{aligned}
D(\mathbf{x}, \mathbf{Q}) &\equiv \sum_{ij} a_{ij}(x_i x_j)^{1/2} + (Q_1 Q_2)^{1/2} \sum_i b_i x_i + (Q_1 Q_3)^{1/2} \sum_i c_i x_i \\
&+ (Q_1 Q_4)^{1/2} \sum_i d_i x_i + (Q_2 Q_3)^{1/2} \sum_i e_i x_i + (Q_2 Q_4)^{1/2} \sum_i f_i x_i \\
&+ (Q_3 Q_4)^{1/2} \sum_i g_i x_i + Q_1 \sum_{ij} m_{ij}(x_i x_j)^{1/2} + Q_2 \sum_{ij} n_{ij}(x_i x_j)^{1/2} \\
&+ Q_3 \sum_{ij} p_{ij}(x_i x_j)^{1/2} + Q_4 \sum_{ij} q_{ij}(x_i x_j)^{1/2} + Q_1^{1/2} \sum_i r_i(x_i) \\
&+ Q_2^{1/2} \sum_i s_i(x_i) + Q_3^{1/2} \sum_i t_i(x_i) + Q_4^{1/2} \sum_i z_i(x_i)
\end{aligned} \tag{3.21}$$

The specification described in (3.21) imposes linear homogeneity in inputs only, which is a property imposed by theory, that is, by the definition of a distance function. All other properties of the technology are flexible, in that even second derivatives are not constant and depend on the data. Coefficients **b**, **c**, **d**, **e**, **f**, **g** are highlighted as they are used to estimate output jointness. These coefficients allow cross-output effects to be scale-dependent, as cross-derivatives and elasticities will depend on both the output and the input levels. Scale dependence is desirable, because cost complementarities can be expected to be more important at lower scales of production.

3.5 Data and results

The data we use are from the Ghana Living Standard Survey Round 4 (GLSS4), a nationally representative multipurpose household survey conducted in 199899. GLSS4 covered 300 randomly selected enumeration areas (EA), defined from the 1984 national census, and surveyed 20 households in each. Of the 6,000 households surveyed, 3,799 were in rural areas. This study focuses on farm households which owned or operated some farm land, of which there were a total of 3,110 in the survey. Among these, 654 households were dropped from our subsample because they did not report quantities of important inputs and/or outputs, or did so inconsistently. For example, some households declared some livestock output (sales or ownconsumption) without reporting any livestock on the farm during the reference period. Another 167 outliers observations in which misreporting was likely had also to be dropped. Our final sample therefore consisted of 2,289 rural households.

The farms in the dataset undertake both farm and nonfarm income activities. Three farm output measures were computed cash crops, food crops, and livestock and other cropsand measured as indices: total value of household output divided by the cross-section median.[26] Livestock output was computed as the sum of in-cash and in-kind incomes from livestock produce (eggs, milk, dairy products, etc.), plus sales and rents of livestock and the value of own consumption of livestock produce. Off-farm output was measured as the sum of all nonfarm revenues. These include revenue from household nonfarm enterprises, incomes from selling water and leasing out/sharecropping land, and wages from employment (including in agriculture).

Table 3.2 provides an overview of farmers production and input use in Ghana. Food crops prevail in most regions, except in those close to urban agglomerates, where off-farm incomes account for approximately 40% of the total value of production. Livestock accounts for an average of only 6.5% of production value. The components of nonfarm income are detailed in Table 3.3. The nonfarm enterprises category includes any business or trade not related to agriculture that is operated by household members; it accounts for most nonfarm income in most regions. Wages from employment also make a large contribution, particularly in southern regions, where they reach 20% of nonfarm income. Revenues from the sale of water and the letting and sharecropping of land appear to be very marginal, but sharecropping seems to have a tangible impact on off-farm incomes in some

[26] Pure quantity indices were also constructed. However, GLSS4 reports many Ghanaian traditional and nonstandard units (which vary by region, such as "box"), most without conversion factors to standard units. Construction of these indices therefore required many assumptions and estimations, so value was used as a proxy for quantity. The sensitivity analysis described later explores the effects of this choice.

regions. Both water sales and land leasing income show very high variability coefficients, indicating that they are an important income source for some households. Remittances are the main source of nonfarm income in the northern and poorest regions of Ghana.

Four input indices were constructed by dividing the measures of land, labor, livestock and operating expenses by their respective sample medians. Land was measured as the number of hectares operated by household members, including plots that are owned, rented or sharecropped as an agricultural input, and plots that are let or sharecropped out as an input of nonfarm income.

In the absence of data on effective labor employedthe hours spent on farm and nonfarm activitieswhich were recorded for households nonfarm enterprises only, family labor supply was used as a proxy, measured as the number of family members aged 12 years or more. Livestock units (as input stock) were evaluated at sale prices. Operating expenses were calculated by adding all purchased inputs, including energy, fertilizers, seeds, etc. Table 3.2 shows little variation in the labor input, whose mean is concentrated around 2. It can also be observed that average plots are very small in almost every region, and the variability is also quite low. The study sample consisted of relatively homogeneous small farms of about 3.5 hectares. There is far more variability in the two other input measures, although some of this is price-driven. As expected, a positive correlation can be observed between regions with high livestock input usage and those with high livestock output.

In addition to inputs and outputs, the distance function was also estimated with several control variables. We used regional dummies to control for unobserved regional-level differences, and dummy variables related to land to check whether the productive process is affected by owning and/or leasing out plots. Household characteristics were also inserted, such as an indicator variable for female-headed households, the age of the household head in linear and squared terms, a housing index to control for housing quality, the average education level of household members,[27] distance from the nearest school, and a dummy variable for households with formal loans.

3.5.1 Sample selection bias

Our estimates are done after dropping about one out of four observations in the original survey, mostly because of inconsistent reporting. To determine whether there is a consistent pattern that could cause significant sample selection bias, Table 3.4 shows probit estimations of the mirror of

[27] Jolliffe (2002) shows that in Ghana average education is a better predictor of household income than education of the head or maximum educational attainment of the household. We alternatively used dummies for shares of household members with different educational attainment levels, and found that the group with between four and eight years of education drives the average effect of education, while the group with less than four years has no effect on the distance.

misreporting, that is, the probability of being in the sample. For Sample 1 in Table 3.4, only inconsistent observations (654) are removed from the original sample of 3,110 farms. Only expenditure level, household labor (working-age members) and remittance receipts are significant. Expenditure level should be interpreted with care, because inconsistent observations are likely to imply inconsistent expenditures figures. Surprisingly, variables that were expected to determine misreporting, such as education variables or farm size, appear as insignificant. This, together with the low predictive power of the regression (sensitivity of 56%) makes it likely that unobservable characteristics of the household and/or the survey implementation (i.e., interviewers characteristics) play a larger role in explaining attrition. Sample 2 in Table 3.4 is more narrowly defined, excluding only the 167 outliers. Here input variables are significant but this is partly by construction, as outliers were identified by their implausibly extreme use of inputs.

If observations are randomly and uniformly dropped from the final sample, knowing the two-stage stratified sample design would allow the weights to be reconstructed and labelled as "neutral-adjusted weights". However, if the probability of being in the sample depends on observable characteristics, as Sample 2 in Table 3.4 suggests, this probability can be used to calculate a new weight.the "probability-adjusted weight": $w_j^* = (p_j^s \cdot \hat{p}_j^a)^{-1} = w_j(\hat{p}_j^a)^{-1}$. This new weight w_j^* is equal to the original household weight (w_j) times the inverse of the probability of being included in the working sample ($\hat{p}_j^a$), which is predicted using Sample 2 in Table 3.4.

In the following regressions, probability-adjusted weights are used in both the summary statistics and the estimation of the distance function.Weighted regressions are usually avoided because, although they provide unbiased and consistent estimators, they reduce efficiency. This study uses probability-adjusted weights because they are correlated with dependent variables as the probits (especially the second) suggest. We conclude that our estimates do not appear to be affected by large selection bias, because there are no large differences in the observed outcomes between using neutral- or probability-adjusted weights and using an unweighted regression but including the inverse Mills ratio (which is not significant).

3.5.2 The results

Table 3.5 presents the technology coefficients estimated by maximum likelihood SUR of the system represented by (3.20) and (3.21), and the controls from the first equationthe distance function normalized by the land input. The system has a very good fit in that most of its technology parameters are highly significant. Most controls have the expected signs. For example, landowners tend to be more efficient, and female-headed households less so. Households with more mature heads are more efficient, but at a decreasing rate, while more remote farms are less efficient. However, the average education of the household is the only control that is statistically significant and, as expected, households with higher average education are found to be more efficient, although there could be reverse causality here, with households achieving higher education because they are more efficient.

Table 3.6 presents the main input and output elasticities of the estimated distance function. Given the highly nonlinear form of some elasticities, bootstrap methods were used for standard errors and hypothesis testing'.[28] The output elasticities presented in the first column of Table 3.6 indicate that, as expected, all marginal costs are positive. The figures also suggest increasing returns to scale, but constant returns cannot be rejected. The DEA analysis also suggests increasing returns, as the ratio of DEA TE under CRS to TE under nonincreasing returns to scale is equal to 1 for 98% of observations.[29] These results may seem surprising, because technological sources of increasing returns are unlikely to be present. Instead, the result could be driven by the difficulty of adjusting to declining land area available per worker. The elasticities by farm size calculated in Table 3.8 show that increasing returns to scale occur in small/medium-sized farms of between 1 and 10 acres (significantly for those between 2.5 and 5 acres), while the smallest and largest farms display decreasing returns to scale. High technical inefficiency makes it difficult to interpret input elasticities. If households were technically efficient, the input elasticity would be exactly equal to the input cost share. In this study, however, it is the cost share under shadow prices that is recovered from the input elasticities, as shown by price ratio, w_2^s/w_1^s in Fig. 3.1. The difference between the technically efficient set point B in the figure and point C, the cost minimizing set, is the "allocative inefficiency". It is hard to estimate allocative inefficiency when input markets are clearly not working fully, so this study did not try to do so. Under shadow cost prices, operating expenses and labor account for similar shares of total output costs, about 34%, while land accounts for 30%, and livestock for less than 0.5%. However, livestock is an important input for smaller farms, particularly those of less than 1 acre, where livestock can amount to 13% of costs at shadow prices, as shown in Table 3.8.

The cross-output elasticities presented in Table 3.7 indicate that cost complementarities are

[28]In a bootstrap of 7,500 replications, the survey design was maintained by performing a two-stage bootstrap, in which clusters were resampled in the first stage, and households in the second. For consistency, the sample size in each stage was adjusted according to the McCarthy and Snowden (1985) procedure; see Shao and Tu, 1995: chapter 6 for details.

[29]See Färe et al. (1994) for details.

present among all outputs. This in turn indicates that there is opportunity for important economies from diversification by rural households. Not surprisingly, the most important cost complementarities are among food crops and livestock, which are the main activities for diversified rural households, that is, specialization tends to be in cash crops.Also important are the cost complementarities between food and cash crops. Cost complementarities with nonfarm activity are all significant, being that with livestock production the largest.

Input technical efficiency, estimated in a first stage by the DEA method, yielded the surprisingly low average of 0.18, as shown in Table 3.6; high inefficiency had been expected because of the generally low levels of education and the missing and imperfect markets. These results should be compared with the estimated TE of farms in other Western Africa countries, such as 0.95 in the Gambia (Chavas et al., 2005), 0.36 to 0.45 for coffee farms in Cameroon (Nyemeck Binam et al., 2003), and 0.77 for rice farms in Nigeria (Idiong, 2007). The estimates for Ghana signify that input sets could be proportionally contracted, on average, to 18% of their original levels and still produce the same amount of output. The high variance of TE shows that households were distributed across the feasible range $(0, 1]$ as shown in Fig. 3.2. In addition, efficiency is not positively correlated to farm size, as could be conjectured; in fact smaller farms are more efficient than larger farms as explained later.

Another important consequence of participation in nonfarm activities is its effect on input demand. It is frequently argued (see for example Katz and Stark, 1986; Haggblade et al., 2007) that income from nonfarm activities, including remittances from migration, alleviates credit constraints. If this were the case, larger nonfarm output would be associated with greater farm input use. Table 3.7 shows the implicit input partial demand elasticities obtained from the distance function.[30] Purchased inputs and workers, which are both shared inputs, expand with nonfarm production; more important, so does land, which is an exclusively agricultural input. These observations are consistent with the cash constraints hypothesis described above. A similar result is found using marginal cost ratios among farm sizes. The ratios of the marginal costs of food crops to nonfarm activities[31] and of cash crops to nonfarm output are higher for the overall sample than for farms of less than 5 acres, implying that smaller farms' involvement in nonfarm activities is relatively less productive. As Eq. (3.12) suggests, this result is consistent with the hypothesis that small farm

[30] The partial input demand elasticities can be obtained by totally differentiating first-order conditions of (3.14), and shown as $\partial \ln x_i / \partial \ln Q_4 = Q_4/x_i \cdot (\partial D/\partial Q4 \cdot \partial D/\partial x_i - \partial^2 D/\partial x_i \partial Q_4)/\partial^2 D/\partial x_i^2$. This expression is nonlinear in the regression coefficients estimated, which prompted the use of bootstrapping techniques for hypothesis testing throughout this study.

[31] Exactly equal to the ratio of distance to output elasticities.

households use nonfarm activities to overcome cash constraints.

3.5.3 Sensitivity analysis

It was important to explore whether the land elasticity is miscalculated as a result of differences in land productivity. To control for this unobserved characteristic, the system was estimated with enumeration area dummies, to capture cluster level differences such as variations in land productivity. In unreported regressions using cluster dummies, it was surprising to find that land elasticity does not change significantly; livestock output is the only elasticity to be significantly reduced.

Another issue that required further examination is the use of production values instead of value-free physical measures of output. If prices were constant throughout Ghana, this would be an innocuous choice, but prices are likely to vary a lot, particularly by distance to markets. The per unit value of agricultural output is expected to be much lower for isolated farms than for those close to markets. The consequences of this price difference were explored assuming that for farm i the gate price of output, p_i^g , is equal to the market price p^m times a deflating function that depends on distance to market: $g(d)$, i.e. $p_i^g = p^m g(di)$, with $g(di) < 1$ and $g'(di) < 0$. For simplicity, $g(di) \equiv 1/(1 + \alpha d_i)$ was assumed, and the sensitivity of the estimated results to different levels of α explored. Distance to markets was proxied by distance to schools; crop and livestock values (input stocks and output) were deflated, and the cost of purchased inputs inflated. In unreported regressions, it was found that most of the elasticities reported in Table 3.6 are surprisingly robust, except for the output elasticity of food crops (Q_2), which is very likely underestimated. This result makes sense, as more isolated farms will specialize in food rather than cash crops because of distance to markets. If the gate value of food crops for these distant farms is lower, this study is underestimating the farms output level and, consequently, overestimating their marginal costs. This overestimation of the marginal cost of food crop production, together with the robustness of the other elasticities means that scale economies are likely to be underestimated; as the α increased, the scale economies became larger, and statistically larger than 1.

The effect of the procedure for removing outliers was also explored by relaxing the cut-off point and allowing more observations into the sample. As the sample grows, the marginal costs of both food and livestock output start to grow, to a point where estimates collapse into economic infeasibility, that is, there are negative marginal costs.

3.5.4 Benchmarking results with stochastic frontier estimation

The second column of Table 3.6 shows the elasticities of distance function (3.21) estimated with a half-normal stochastic frontier model, as described in (3.17). The results indicate that the half-normal stochastic frontier model clearly fails to estimate the underlying technology. The implicit negative marginal costs and negative returns to scale estimated are violations of basic economic behavior. We believe that the linear stochastic model fails for three reasons. First, as shown, estimation of the linear stochastic distance function is inconsistent in proportion to the level of inefficiency, which in this case is high. Second, *a posteriori*, it can be seen that the half-normal distribution of the input distance is an inadequate assumption. Given the treatment of outliers, the DEA technical inefficiency measure could be questioned regarding the levels, but the underlying distribution of efficiency calculated and shown in Fig. 3.2 is harder to question. This distribution cannot fit a half-normal or exponential distribution, as shown by a simulated half-normal distribution in the same figure. The third reason for failure of the stochastic frontier model is that the input distance is too high. Stochastic frontier methods are an elegant way of identifying the level of technical inefficiency from the residual. When the level of technical inefficiency is very high, this method may be asking too much of the residual. The econometric lessons learned in this study call for care when using stochastic frontier methods in the context of microeconomic development analysis.

3.6 Conclusions

The aim of this study was to identify the microeconomic effects of an expanding nonfarm sector in rural Ghana, focusing on possible complementarities between nonfarm activity and farm production costs and the demand for farm inputs. We test for these effects in a context where many households are far below the estimated efficiency frontier, using techniques that emphasize the need for careful attention to the distribution of TE and other sources of error in estimation.

Our first main result is that RNF activity offered significant economies from diversification by rural households, with important cost complementarities between the nonfarm and farm sectors, especially for livestock and food crops. This is a very robust finding that held throughout various sensitivity analyses. The second main result is that RNF production influenced household demand for farm inputs. The evidence found is consistent with the hypothesis that the nonfarm sector eases household cash constraints, as expansion of the nonfarm sector increases the demand for inputs, including those that are farm-specific, such as land.

Finally, we note that the microeconomic linkages we study in this article may differ from macroeconomic linkages estimated with sector-level data, such as the results obtained in Blunch and Verner (2006). From a policy perspective, it is important to know more about both kinds of linkages, which have clear implications for growth and poverty.

References

Blunch, N.-H. and D. Verner (2006) "Shared sectoral growth versus the dual economy model: Evidence from Côte dIvoire, Ghana, and Zimbabwe", *African Dev. Rev./Revue Africaine de Developpement*, **18(3)**, 283308.

Charnes, A., W.W. Cooper and E. Rhodes (1978) "Measuring the efficiency of decision-making units", *Eur. J. Oper. Res.*, **2(6)**: 429444.

Coelli, T. (2000) "On the Econometric Estimation of the Distance Function Representation of a Production Technology", Working Paper Louvain: 24.

Coelli, T., G. Hajargasht and C.A. Lovell (2007) "Econometric Estimation of an Input Distance Function in a System of Equations" Working Paper, Centre for Efficiency and Productivity Analysis Brisbane: 48.

Davis, B., T. Reardon, K. Stamoulis and P. Winters (2002) *Promoting farm/non-farm linkages for rural development. Case Studies from Africa and Latin America*, FAO, Rome, pp. 121/170.

Davis, B., P. Winters, G. Carletto, K. Covarrubias, E. Quinones, A. Zezza, K. Stamoulis, G. Bonomi and S. DiGiuseppe (2007) "Rural Income Generating Activities: A Cross Country Comparison", *Background paper for the World Development Report 2008*, Rome, FAO.

Färe, R., S. Grosskopf and C. A. Lovell (1994) *Production frontiers*, Cambridge University Press.

Färe R.S. and D. Primont (1995) *Multi-Output Production and Duality*, Theory and Applications, Kluwer Academic Publishers, Boston.

Farrell, M.J. (1957) "The measurement of productive efficiency", *J. R. Statistic. Soc.*, **A-120(3)**: 253-281.

Ghana Statistical Service (2000) "Poverty trends in Ghana in the 1990s" in *Ghana Living Standards Survey Round Four (GLSS 4) 1998/99*, Accra.

Gorman, I. E. (1985) "Conditions for Economies of Scope in the Presence of Fixed Costs", *RAND J. Econ.*, **16(3)**: 431-36.

Haggblade, S., P. Hazell and J. Brown (1989), "Farm-Non Farm Linkages in Rural Sub-Saharan Africa", *World Development*, **17(8)**: 1173-1202.

Haggblade, S., P. Hazell and T. Reardon (Eds) (2007) *Transforming the Rural Nonfarm Economy: Opportunities and Threats in the Developing World*, Baltimore, The Johns Hopkins University Press.

Hirschman, A. O. (1958) *The Strategy of Economic Development*, New Haven, Connecticut, Yale University Press.

Idiong, I.C. (2007) "Estimation of farm level technical efficiency in small-scale swamp", *World J. Agric. Sci.*, **3(5)**: 653658.

Jolliffe, D. (2002) "Whose education matters in the determination of household income? Evidence from a developing country", *Econ. Dev. Cult. Change*, **50(2)**: 287312.

Katz, E. and O. Stark (1986) "Labor migration and risk aversion in less developed countries" *J. Labor Econ.*, **4(1)**: 134149.

Kumbhakar S.C. and C.A. Lovell (2000) *Stochastic Frontier Analysis*, Cambridge University Press.

Kuznets, S.S. (1957) "Quantitative aspects of the economic growth of nations II", *Econ. Dev. Cult. Change*, **4(Supplement)**: 311.

Lewis, W.A. (1954) "Economic development with unlimited supplies of labor", *The Manchester School*, **22(2)**: 139191.

McCarthy P.J. and C.B. Snowden (1985) "The Bootstrap and Finite Population Sampling", *Vital and Health Statistics*, **Series 2, 95**, Public Health Service Publication, Washington DC, U.S. Government Printing Office, 1-23.

Newman, C. and S. Canagarajah (2000) "Non-farm employment, poverty, and gender linkages: evidence from Ghana and Uganda", *Policy Research Working Paper*, **2367**, World Bank: August.

Nyemeck Binam, J., K. Sylla, I. Diarra and G. Nyambi (2003) "Factors affecting technical efficiency among coffee farmers in Côte d'Ivoire: Evidence from the centre west region", *African Dev. Rev./Revue Africaine de Developpement*, **15(1)**: 6676.

Reardon, T., J. Berdegu, C.B. Barret and K. Stamoulis (2007) "Household Income Diversification into Rural Nonfarm Activities", in *Transforming the Rural Nonfarm Economy. Opportunities and Threats in the Developing World*, S. Haggblade, P. Hazell and T. Reardon, Eds., Baltimore and London, The John Hopkins University Press, pp.115-140.

Reardon, T., K. Stamoulis, M.E. Cruz, A. Balisacan, J. Berdegu and B. Banks (1998) "Rural Non-farm Income in Developing Countries" in *FAO: the State of Food and Agriculture*, FAO, Rome, pp. 283-356.

Shao, J. and D. Tu (1995) *The Jackknife and Bootstrap, Series in Statistics*, Springer, New York, Heidelberg and London.

Singh, I., L. Squire and J. Strauss (1986) *Agricultural Household Models. Extensions, applications and policy.* Baltimore and London, The John Hopkins University Press for the World Bank.

Valdés, A. and W. Foster (2003) "The Positive Externalities of Chilean Agriculture: The Significance of its Growth and Export Orientation" in *ROA Project*, FAO, Rome.

Vogel94 Vogel, S.J. (1994) "Structural Changes in Agriculture: Production Linkages and Agricultural Demand-Led Industrialization" *Oxford Econ. Papers*, **46(1)**: 136-56.

3.7 Tables

Table 3.1: Key economic and social indicators from Ghana

	1987/88		**1991/92**		**1998/99**
Per capita GDP[1]	202.56		216.91		244.17
Mean yearly growth rate		1.73		1.71	
Agriculture, value added (% GDP)	50.5		45.5		36
Per capita agricultural value added[1]	84.49		82.58		87.59
Mean yearly growth rate		-.57		.85	
Per capita agricultural production[2]	70.05		84.2		93.7
Mean yearly growth rate		4.71		1.54	
Population, total	14,439,140		16,145,312		19,221,380
Rural population (%)	65.5		62.5		57.5
Households income shares (%)[3]					
Farm	66.46 [5]		60.88		42.08
Nonfarm self-employment	16.16 [5]		15.49		28.67
Wage employment (including agric.)	17.56 [5]		23.62		29.25
Rural households income shares[3] **(%)**					
Farm			77.00		58.31
Nonfarm self-employment			11.93		23.64
Wage employment (including agric.)			11.07		18.05
Per capita expenditure[4] **- National**			798,594		993,897
Mean yearly growth rate				3.17	
Per capita expenditure[4] **- Rural**			658,882		773,093
Mean yearly growth rate				2.31	
Poverty incidence - National (%)			51.7		39.5
Poverty incidence - Rural (%)			63.6		49.5

Notes: 1) Constant 2000 US$. 2) Production index. 3) Calculated as shares of aggregate household income, excluding transfers and miscellaneous sources of income. 4) In 1999 local currency (cedi). 5) Income shares from Newman et al. (2000), not exactly comparable to 1991/92 and 1998/99 income shares.
Sources: World Development Indicators from the World Bank.91/92 and 98/99 income shares, poverty indexes, per capita expenditures from GLSS3 & GLSS4 and Ghana Statistical Service (2000). Agricultural production indexes from FAOSTAT.

Table 3.2: Output and input compositions (coefficients of variation in parentheses)

(a) Output composition

Region	Total[2]	Q_1	Q_2	Q_3	Q_4
Western	6,246,071	26.6	39.8	2.5	31.1
(240)[1]	(3.3)	(1.0)	(0.7)	(3.8)	(1.1)
Central	3,484,720	11.7	42.2	6.0	40.1
(292)	(1.5)	(1.5)	(0.8)	(2.4)	(0.9)
Greater Accra	3,386,875	0.7	43.2	0.5	55.5
(27)	(1.4)	(3.4)	(0.9)	(3.3)	(0.7)
Eastern	3,474,006	5.4	37.5	8.8	48.3
(259)	(1.8)	(2.4)	(0.9)	(2.4)	(0.8)
Volta	3,414,416	9.6	53.4	5.2	31.9
(357)	(1.2)	(1.7)	(0.6)	(2.3)	(1.1)
Ashanti	3,883,818	8.5	56.7	2.7	32.1
(405)	(1.7)	(2.0)	(0.6)	(3.1)	(1.1)
Brong Ahafo	2,852,970	5.8	68.8	1.5	23.9
(269)	(1.5)	(2.5)	(0.4)	(3.0)	(1.2)
Northern	1,734,735	18.9	51.3	11.0	18.7
(188)	(1.7)	(1.0)	(0.5)	(1.3)	(1.5)
Upper East	1,494,256	23.4	55.7	9.7	11.2
(53)	(3.8)	(0.8)	(0.4)	(1.2)	(2.3)
Upper West	1,955,682	14.6	53.5	11.3	20.7
(199)	(1.4)	(0.9)	(0.5)	(1.1)	(1.5)
Total	3,422,314	12.8	50.6	5.8	30.8
(2289)	(2.6)	(1.5)	(0.6)	(2.3)	(1.1)

Notes: Averages calculated using probability adjusted weights.
1) Observations #. 2) Total value in local currency.
3) Q_1, Q_2, Q_3, Q_4 shares in percentages.
Q_1 = cash crop; Q_2 = food crop; Q_3 = livestock;
Q_4 = off-farm income.

(b) Input composition

Region[1]	x_1	x_2	x_3	x_4
Western	3.8	398,352	3.06	532,107
(240)	(0.92)	(2.73)	(0.57)	(1.62)
Central	3.06	177,339	2.55	452,628
(292)	(0.87)	(2.28)	(0.56)	(1.66)
Greater Accra	1.17	126,134	2.55	1,243,060
(27)	(0.49)	(1.29)	(0.49)	(1.2)
Eastern	1.42	439,952	3.48	1,278,233
(259)	(1.16)	(5.25)	(0.59)	(3.28)
Volta	1.8	236,497	3.19	388,986
(357)	(1.5)	(2.16)	(0.52)	(1.2)
Ashanti	2.8	261,234	3.24	554,466
(405)	(0.98)	(3.1)	(0.58)	(4.44)
Brong Ahafo	3.61	166,559	2.55	589,351
(269)	(1.09)	(1.6)	(0.59)	(1.61)
Northern	2.69	172,377	3.25	1,635,155
(188)	(0.66)	(1.3)	(0.49)	(1.13)
Upper East	2.71	70,383	4.89	1,665,500
(53)	(0.41)	(3.57)	(0.41)	(0.78)
Upper West	2.1	97,738	3.07	1,044,195
(199)	(0.58)	(2.36)	(0.45)	(1.28)
Total	2.67	245,962	3.12	864,146
(2289)	(1.05)	(3.97)	(0.56)	(2.30)

Notes: x_1 = land size (hectares); x_2 = operating expenses (LCU); x_3 = # workers; x_4 = livestock value (LCU).

Table 3.3: Nonfarm activities composition: mean shares (coefficients of variation in parentheses)

Region (observations)	**Nonfarm[1] income**	**Nonfarm enterprises**	**Wages**	**Water sold**	**Land rents**	**Remittances**	**Other**
Western	2,153,357	45.7	18.6	0.00	3.13	29.2	3.36
(240)	(3.12)	(1.05)	(1.98)	(.)	(5.34)	(1.52)	(4.95)
Central	2,219,509	50.1	9.34	0.55	3.11	30.9	6.04
(292)	(2.30)	(0.94)	(2.84)	(13.5)	(5.1)	(1.37)	(3.32)
Greater Accra	2,489,469	41.4	11.6	0.00	10.9	32.1	4.05
(27)	(1.91)	(1.09)	(2.69)	(.)	(2.45)	(1.31)	(3.14)
Eastern	2,288,388	58.8	10.2	0.00	0.40	22.7	7.83
(259)	(2.21)	(0.78)	(2.68)	(.)	(9.24)	(1.74)	(3.23)
Volta	1,459,130	38.1	13.9	0.19	8.93	33.9	4.99
(357)	(2.22)	(1.20)	(2.34)	(13.5)	(2.93)	(1.3)	(3.98)
Ashanti	2,112,235	28.9	8.00	0.03	5.89	38.1	19.1
(405)	(2.84)	(1.49)	(3.12)	(13.6)	(3.48)	(1.16)	(1.91)
Brong Ahafo	870,408	27.4	19.00	0.00	3.80	48.9	0.88
(269)	(3.20)	(1.56)	(2.01)	(.)	(4.14)	(0.96)	(8.95)
Northern	483,584	36.7	6.68	0.00	0.00	45.7	10.9
(188)	(2.28)	(1.28)	(3.49)	(.)	(.)	(1.07)	(2.62)
Upper East	867,574	8.7	2.42	0.00	0.00	41.2	47.8
(53)	(6.48)	(3.37)	(6.59)	(.)	(.)	(1.15)	(1.01)
Upper West	742,933	26.0	6.52	0.00	0.00	48.3	19.2
(199)	(2.96)	(1.62)	(3.61)	(.)	(.)	(0.95)	(1.82)
Total	1,569,058	39.4	11.8	0.10	3.76	35.9	8.97
(2289)	(2.94)	(1.18)	(2.56)	(26.9)	(4.53)	(1.25)	(2.92)

Notes: Averages calculated using probability adjusted weights. 1) yearly average per household (LCU). Other columns represent nonfarm income shares.

Table 3.4: Sample selection probits (marginal effects reported, standard errors in parentheses)

Variable	**Sample 1**		**Sample 2**	
Tot PC cons.	4.25e-07 ***	(1.45e-07)	4.49e-07 ***	(1.57e-07)
Food cons. share	0.069	(0.062)	0.170 **	(0.068)
HH labor	0.014 **	(0.006)	0.013 **	(0.007)
Operated landsize	0.004	(0.003)	0.010 ***	(0.003)
Land-owner	0.018	(0.016)	0.035 *	(0.018)
Land rented-out	-0.030	(0.064)	-0.077	(0.071)
Female head	0.012	(0.018)	-0.038 *	(0.020)
Age of head	0.001	(0.003)	0.004	(0.003)
(Age of head)^2	-0.00002	(0.00003)	-0.00005	(0.00003)
Average education of the hh	-0.005	(0.003)	-0.005	(0.003)
Head reads English	0.012	(0.011)	0.005	(0.012)
Head reads Ghanaian	-0.008	(0.010)	-0.003	(0.011)
Member is an apprentice	0.005	(0.011)	-0.004	(0.011)
Training	0.040	(0.041)	0.001	(0.042)
Nr. of hospitalized hh members	0.008	(0.013)	0.005	(0.014)
Receives remittances	0.042 ***	(0.015)	0.051 ***	(0.017)
Min. distance school	.0.00002	(0.00006)	2.36e-06	(0.0001)
Regions				
Western	-0.163 ***	(0.050)	-0.182 ***	(0.050)
Central	-0.088 **	(0.044)	-0.017 ***	(0.046)
Greater Accra	-0.103	(0.096)	-0.142	(0.097)
Eastern	-0.175 ***	(0.048)	-0.175 ***	(0.047)
Volta	-0.114 ***	(0.044)	-0.111 ***	(0.045)
Ashanti	-0.119 ***	(0.044)	-0.129 ***	(0.045)
Brong Ahafo	-0.136 ***	(0.048)	-0.102 **	(0.048)
Northern	-0.100 **	(0.048)	-0.072	(0.049)
Upper East	-0.375 ***	(0.066)	-0.324 ***	(0.064)
No. of obs.	3110		3110	
Log-likelihood	-1543.04		-1740.47	
$LR - \chi^2$	91.81		109.17	
Pseudo R^2	0.029		0.030	
Sensitivity (%)	57.83		56.44	

Notes: Sample 1 = 0 only for inconsistent observations (654 obs.).
Sample2 = 0 for inconsistent observations and outliers (821 obs.).

Table 3.5: **Maximum Likelihood SUR technology parameters estimates[1] (2289 observations, standard errors in parentheses)**

Western	4.358**	a22	-5.102***	f1	0.662***	n22	0.651***	q24	0.369***
	(1.814)		(0.482)		(0.095)		(0.066)		(0.088)
Central	4.093**	a23	10.948***	f2	-0.063	n23	-1.485***	q33	3.175***
	(1.826)		(0.747)		(0.107)		(0.175)		(0.191)
Greater Accra	9.975**	a24	-2.782***	f3	2.064***	n24	0.017	q34	-1.439***
	(4.922)		(0.451)		(0.270)		(0.124)		(0.151)
Eastern	8.853***	a33	12.919***	f4	-0.679***	n33	2.863***	q44	0.040
	(1.814)		(0.637)		(0.153)		(0.263)		(0.079)
Volta	2.582	a34	9.643***	g1	0.379**	n34	-0.978***	r1	-2.134***
	(1.775)		(0.701)		(0.166)		(0.161)		(0.189)
Ashanti	4.723***	a44	-5.262***	g2	-0.395***	n44	-0.240**	r2	0.604***
	(1.813)		(0.464)		(0.056)		(0.120)		(0.146)
Brong Ahafo	6.558***	b1	0.442***	g3	3.926***	p11	-0.082	r3	-8.313***
	(1.803)		(0.075)		(0.186)		(0.159)		(0.687)
Northern	0.456	b2	-0.272***	g4	-0.111	p12	-0.180**	r4	0.698*
	(1.702)		(0.082)		(0.111)		(0.088)		(0.270)
Upper East	-0.004	b3	2.306***	m11	0.195**	p13	0.462	s1	-3.027***
	(2.442)		(0.320)		(0.079)		(0.331)		(0.222)
Land Owner	-0.452	b4	-0.022	m12	-0.241***	p14	0.125	s2	-0.607*
	(0.837)		(0.132)		(0.132)		(0.087)		(0.312)
Land Rent-out	0.560	c1	0.460***	m13	0.043	p22	-0.084***	s3	-11.763***
	(3.163)		(0.142)		(0.259)		(0.016)		(0.642)
Female Head	0.028	c2	-0.160***	m14	-0.040	p23	-1.301***	s4	3.240***
	(0.898)		(0.045)		(0.137)		(0.199)		(0.346)
Age of Head	-0.083	c3	1.711***	m22	0.131***	p24	0.474***	t1	-2.775***
	(0.070)		(0.091)		(0.028)		(0.049)		(0.397)
(Age of Head)^2	0.001	c4	-0.138	m23	-0.255	p33	2.287***	t2	1.250***
	(0.001)		(0.090)		(0.235)		(0.377)		(0.177)
Highest educ	-0.368***	d1	0.205	m24	0.101	p34	-0.988***	t3	-13.223***
	(0.128)		(0.132)		(0.096)		(0.184)		(0.605)
Loan	-0.776	d2	-0.239***	m33	0.472	p44	0.032	t4	1.560***
	(0.834)		(0.051)		(0.408)		(0032)		(0.181)
Min. distance	0.002	d3	0.948***	m34	-0.067	q11	0.788***	z1	-3.465***
to school	(0.003)		(0.320)		(0.386)		(0.145)		(0.302)
Housing index	-0.273	d4	0.238*	m44	-0.162	q12	-0.307***	z2	0.932***
	(0.362)		(0.131)		(0.108)		(0.109)		(0.231)
a11	1.751***	e1	1.039***	n11	0.734***	q13	-1.112***	z3	-12.494***
	(0.348)		(0.159)		(0.089)		(0.197)		(0.549)
a12	10.523***	e2	0.215***	n12	-0.926***	q14	-0.113	z4	1.365***
	(0.583)		(0.072)		(0.111)		(0.165)		(0.388)
a13	8.719***	e3	3.018***	n13	-0.814***	q22	0.128***		
	(0.702)		(0.263)		(0.163)		(0.028)		
a14	-2.154***	e4	-0.752***	n14	0.160	q23	-0.994***		
	(0.551)		(0.083)		(0.113)		(0.152)		

Notes: ***99%, **95%, *90% confidence level.
1) Estimates of the control parameters from the first equation, the distance function normalized by the land input.

Table 3.6: **Input-output elasticities (full sample, 2,289 observations)**

Elasticities	**ML SUR estimates**		**Half Normal stochastic Frontier estimates**	
	Value	**Std.Error**	**Value**	**Std.Error**
ε_{D,Q_1}	-0.078	0.201	0.243 ***	0.051
ε_{D,Q_2}	-0.459 ***	0.228	0.015	0.040
ε_{D,Q_3}	-0.112	0.265	-0.204 ***	0.068
ε_{D,Q_4}	-0.259 ***	0.131	0.078 **	0.034
$\sum_i \varepsilon_{D,Q_i} = -1$	0.092	0.633	1.133 ***	0.102
ε_{D,x_1}	0.331 ***	0.072	0.657 ***	0.129
ε_{D,x_2}	0.356 ***	0.122	0.027	0.035
ε_{D,x_3}	0.307 **	0.109	0.341 ***	0.053
ε_{D,x_4}	0.006	0.062	-0.025	0.029
Technical efficiency[1]	0.182	0.194	0.999	0.002

Notes: Q_1=cash crops, Q_2=food crops, Q_3=livestock, Q_4=off-farm
x_1=land, x_2=operating expenses, x_3=workers, x_4=livestock
Standard errors and hypothesis testing on the first column is based on the bootstrapped empirical distribution of each statistic (B = 7500).
***99%, **95%, *90% confidence level.
(1) In the SUR columns DEA estimates are reported; in the frontier column, technical efficiency is calculated with the estimated one-sided error of the stochastic frontier model.

Table 3.7: Cross-term elasticities

(a) Cost complementarities

	Cash crops	**Food crops**	**Livestock**
Food crops	0.047 ***		
	(0.024)		
Livestock	0.044 ***	0.089 ***	
	(0.026)	(0.041)	
Non-farm	0.017 ***	0.032 ***	0.055 ***
	(0.016)	(0.025)	(0.057)

(b) Input responses to nonfarm output expansion

	Land size	**Purchased inputs**	**Workers**	**Livestock**
$\partial \ln x_i / \partial \ln Q_4$	13.391 ***	19.748 ***	16.549 **	-3.034
	(3.914)	(6.663)	(106.684)	(1323.196)

Notes: Standard errors and hypothesis testing based on a bootstrapped empirical distribution of each statistic (B = 7500). ***99%, **95%, *90% confidence level.

Table 3.8: **Elasticities by farm size**

Elasticities	Less than 1 acre 185 obs.		Between 1 and 2.5 acres 358 obs.		Between 2.5 and 5 acres 529 obs.	
	Value	**Std.Error**	**Value**	**Std.Error**	**Value**	**Std.Error**
ε_{D,Q_1}	-0.078	0.294	-0.031	0.033	-0.042 *	0.033
ε_{D,Q_2}	-1.076 ***	4.855	-0.240 ***	0.082	-0.263 ***	0.065
ε_{D,Q_3}	-0.103	0.916	-0.318 **	0.239	-0.098 **	0.074
ε_{D,Q_4}	-0.457 ***	1.993	-0.246 ***	0.115	-0.185 ***	0.062
$\sum_i \varepsilon_{D,Q_i} = -1$	-0.715 **	7.320	0.165	0.375	0.412 **	0.152
ε_{D,x_1}	0.394 ***	0.992	0.389 ***	0.082	0.313 ***	0.038
ε_{D,x_2}	0.314	0.472	0.310 ***	0.065	0.346 ***	0.047
ε_{D,x_3}	0.160	0.747	0.247 **	0.078	0.304 ***	0.047
ε_{D,x_4}	0.132	0.285	0.054	0.052	0.030 *	0.084
TE[1]	0.375	0.314	0.204	0.214	0.159	0.163
	Between 5 and 10 acres 550 obs.		**Greater than 10 acres 475 obs.**			
ε_{D,Q_1}	-0.084	2.175	-0.211	70.437		
ε_{D,Q_2}	-0.501 ***	2.402	-1.173 **	70.242		
ε_{D,Q_3}	-0.158	3.342	0.018	24.629		
ε_{D,Q_4}	-0.248 **	1.316	-0.292	21.318		
$\sum_i \varepsilon_{D,Q_i} = -1$	0.009	8.79	-0.659	183.732		
ε_{D,x_1}	0.371 **	0.756	0.293	7.873		
ε_{D,x_2}	0.303 **	0.968	0.384	10.096		
ε_{D,x_3}	0.316	1.188	0.396	10.488		
ε_{D,x_4}	0.009	0.619	-0.073	5.754		
TE[1]	0.165	0.165	0.157	0.164		

Notes: Hypothesis testing based on the bootstrapped empirical distribution of each statistic (B = 7500). ***99%, **95%, *90% confidence level. 1) DEA estimates of technical efficiciency

3.8 Figures

Figure 3.1: **Production and Efficiency**

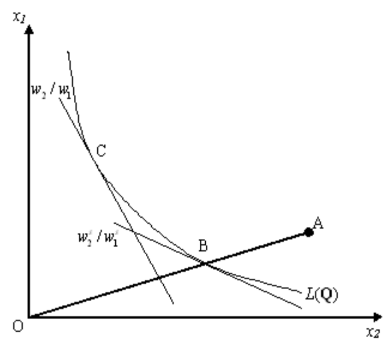


Figure 3.2: **Calculated and Simulated Technical Efficiency**