Competitive, but too small - productivity and entry-exit determinants in European business services

Kox, Henk L.M. and Leeuwen, George van and Wiel, Henry van der

CPB Netherlands Bureau for Economic Policy Analysis, Statistics Netherlands

1 July 2010

Competitive, but too small

Productivity and entry-exit determinants in European business services

Henk Kox, George van Leeuwen and Henry van der Wiel

Discussion paper (201015)

Statistics Netherlands

The Hague/Heerlen, 2010

Explanation of symbols

.	= data not available
*	= provisional figure
**	= revised provisional figure
x	= publication prohibited (confidential figure)
–	= nil or less than half of unit concerned
–	= (between two figures) inclusive
0 (0,0)	= less than half of unit concerned
blank	= not applicable
2008–2009	= 2008 to 2009 inclusive
2008/2009	= average of 2008 up to and including 2009
2008/’09	= crop year, financial year, school year etc. beginning in 2008 and ending in 2009
2006/’07–2008/’09	= crop year, financial year, etc. 2006/’07 to 2008/’09 inclusive

Due to rounding, some totals may not correspond with the sum of the separate figures.

Publisher
Statistics Netherlands
Henri Faasdreef 312
2492 JP The Hague

Prepress
Statistics Netherlands - Grafimedia

Cover
TelDesign, Rotterdam

Information
Telephone +31 88 570 70 70
Telefax +31 70 337 59 94
Via contact form: www.cbs.nl/information

Where to order
E-mail: verkoop@cbs.nl
Telefax +31 45 570 62 68

Internet
www.cbs.nl

ISSN: 1572-0314

60083201015 X-10

Competitive, but too small

Productivity and entry-exit determinants in European business services

Henk Kox[#)], George van Leeuwen[&)] and Henry van der Wiel[*)]

Abstract:

The paper investigates whether scale effects, market structure, and regulation determine the poor productivity performance of the European business services industry. We apply parametric and nonparametric methods to estimate the productivity frontier and subsequently explain the distance of firms to the productivity frontier by market characteristics, entry- and exit dynamics and national regulation. The frontier is assessed using detailed industry data panel for 13 EU countries. Our estimates suggest that most scale advantages are exhausted after reaching a size of 20 employees. This scale inefficiency is persistent over time and points to weak competitive selection. Market and regulation characteristics explain the persistence of X-inefficiency (sub-optimal productivity relative to the industry frontier). More entry and exit are favourable for productivity performance, while higher market concentration works out negatively. Regulatory differences also appear to explain part of the business services' productivity performance. In particular regulation-caused exit and labour reallocation costs have significant and large negative impacts on the process of competitive selection and hence on productivity performance. Overall we find that the most efficient scale in business services is close to 20 employees and that scale inefficiencies show a hump-shape pattern with strong potential scale economies for the smallest firms and diseconomies of scale for the largest firms. The smallest firms operate under competitive conditions, but they are too small to be efficient. And since this conclusion holds for about 95 out of every 100 European business services firms, this factor weighs heavily for the overall productivity performance of this industry.

Key words: productivity; frontier models; scale efficiency; market selection; entry-exit; regulation; EU; business services

JEL codes: **L1, L5, D2, L8**

Acknowledgements
We thank Bert Balk, Eric Bartelsman, Pierre Konings, and Bas ter Weel for their useful comments on earlier versions of this paper. We have also benefited from comments by participants at seminars at the European Commission (DG/IM, Brussels) and CPB (The Hague). Remaining flaws in the paper are ours.

#) CPB Netherlands Bureau for Economic Policy Analysis, P.O. Box 80510, 2508 GM The Hague, Netherlands, email: h.l.m.kox@cpb.nl (corresponding author)

&) Statistics Netherlands, The Hague, Netherlands.

*) CPB Netherlands Bureau for Economic Policy Analysis / CentER (Tilburg University).

1. Introduction

Business services is an industry that accounts for 11 per cent of total market-sector employment in the European Union (EU). The business services industry itself has a stagnating productivity growth. Between 1979 and 2003, its annual productivity growth amounted to −0.3 per cent. This compares badly with the 1.6 per cent average productivity growth in the EU countries.[1] Business services form a large share of total intermediary inputs in the EU countries, so its weak productivity-growth record is no good news for the rest of the European economy. The sector is at risk of becoming a drag on average productivity growth in the EU, with the so-called Baumol Disease lurking around.

This paper investigates the structural causes of the low productivity performance in the European business services industry. In particular, we analyse how the interaction of scale effects, market structure, entry-exit selection, and regulation affect the productivity performance of this industry.

Earlier research by Barone *et al*. (2008) finds that a lack of production efficiency in professional services has significant negative effects on the production efficiency of downstream industries, an effect that even holds for a restricted sample of high-income countries. The effect on aggregate growth may however be mitigated in several ways. Oulton (2001) has shown that the comprehensive contribution of business services to aggregate growth may still be positive, when the price of business services keeps falling compared to the wages in the outsourcing industries. This process works only if the business services industry passes on its productivity gains (however small they may be) to their clients in the form of lower prices. A further mitigating effect is the role of IT and other business services for the innovation process in the rest of the economy. Several authors show that the business services industry generates positive technology spillovers for the rest of the economy (Van Leeuwen 2008; Hempell *et al.* 2002; Antonelli 1999). Others argue that despite a virtual own productivity stagnation, business services may still positively contribute to aggregate growth if the extent of its innovation spillovers to other sectors of the economy is maintained (Kox, 2004; Baker *et al*., 2008). That such positive technological spillovers to the rest of the economy exist is shown empirically by Camacho and Rodriguez (2007) and Guerrieri (2005).

The contribution of our paper to the literature is that we explain the productivity performance of European business services from structural factors like market structure, scale (dis-)economies, entry- and exit dynamics and national regulation. We proceed in two steps. In the first step we estimate a productivity frontier per sub-sector and size class by parametric and nonparametric methods, using a data panel for thirteen EU countries. In a next step we explain the productivity distance of business services firms to the

[1] Rubalcaba et al. (2007) show that the productivity growth stagnation in business services cannot be ascribed to technologically backward branches: the productivity-growth record hardly differs between knowledge-intensive business services with high human-capital content and the more standardised business services that employ lots of less-skilled labour.

productivity frontier by including in our model structural determinants of scale efficiency, market structure, entry- and exit dynamics and national regulatory features.

Our main findings are the following. The smallest size class that represents more than 90 per cent of all business services firms in the EU and about one-third of total employment appears to be very competitive. Small firms with 1-9 workers have tiny market shares and they appear to use very similar technologies as larger firms. However, compared to the most efficient size class (50-249 workers) these firms appear to have a huge scale inefficiency that negatively affects their productivity performance. The scale inefficiency pattern is persistent over time, which points to weak competitive selection. We find that the persistence of sub-optimal productivity relative to the industry frontier is explained by market characteristics and national regulation characteristics. A higher regulation intensity appears to lower productivity performance. More market entry and exit of firms correlates positively with productivity performance, while higher market concentration works out negatively.

The structure of the paper is as follows. Section 2 starts a brief review of the scarce literature on the productivity determinants in services. In section 3 we present the two testable empirical models: a global stochastic frontier model with deterministic features, and a non-parametric data-envelopment model that allows more flexibility in the analysis of scale effects. Section 4 describes our data strategy; together with some descriptive statistics. Section 5 presents the results of the econometric tests, and section 6 summarises the main findings regarding the structural productivity determinants and some possible implications for economic policy.

2. Competitive selection in business services: literature review

The literature offers a number of candidate explanations for stagnating productivity growth in the business services industry. The 'usual suspects' are a lack of competition, weak entry-exit selection, and regulatory barriers. Bartelsman *et al*. (2000) further mention the role of scale efficiency, management and ownership, the quality of the workforce and technology as possible explanations for productivity patterns in industries. Grönroos *et al*. (2004) and Viitamo (2007) somewhat speculatively argue that business services productivity is badly measured, because customer participation in the service production process of the services is underrated. It is not evident how workforce and management quality, or measurement error could explain differences between services sectors and between countries (EU-USA). In this review we focus on three groups of explanatory factors: (a) scale inefficiency; (b) market structure and dynamic entry-exit selection; and (c) regulatory barriers.

2.1 Scale inefficiency

Returns to scale, or scale elasticity, can be considered as a measurement of the increase in output relative to a proportional increase in all inputs. Scale effects are evaluated as marginal changes at a point in the output-input space. In case of constant returns to scale the output increases with the same amount as the increase in inputs. If scale effects, however, exist, an output increase (Δy) is a function of the change in inputs (Δx) and the already achieved level of inputs (x). Hence, the cost function of firms is sub-additive in case of scale economies: it costs less (more) to produce the various output elements together than to produce them separately (Frisch 1965). Within one industry, scale economies may differ between groups of firms depending on the technology that they (can) apply. Variable or 'local' scale economies exist when the range of relevant technologies differs between size classes. It means that the output elasticity of at least one input is positive over some range of input size, while being negative over another range of input size.

The market structure for a services sector may be such that efficient production and distribution requires some minimum-efficient scale. Operating below this threshold either makes average costs too high given market prices, or otherwise the delivered service is too inefficient for being acceptable to clients. Scale diseconomies then have a negative effect on the productivity. Compared to manufacturing, scale economies in services are much less investigated, partly related to data availability problems (cf. Triplett et al., 2004; Diewert 2005). Static scale effects in network services (transport, banking, payment services, retail distribution and telecommunication) are reasonably documented, even though economies of scale and economies of network adoption are not always easy to distinguish. Pels *et al*. (2003), studying scale economies in airports, find that the average European airport operates under increasing returns to scale in producing passenger movements. Schure *et al.* (1999) conclude that European banks experience positive scale economies up to a balance sheet total of 600 million euros, but that the effects strongly diminish at larger size. Nevertheless, they find that the average level of X-inefficiency of European banks exceeded 16 per cent of costs. Static scale effects have also been documented for telecommunications (Bloch *et al.* 2001). Studies on static scale economies in non-network services like business services are scarce. Software producing services industry may display considerable economies of scale, because of the relation between relatively high sunk development costs and almost zero marginal costs of software multiplication (Shy 2001). For European business services industry, Kox *et al.* (2007) find that unexploited scale effects appear to be associated with imperfect competition. Silk *et al*. (2003) examined the scale and scope economies in advertising and marketing services; they conclude that scale efficiency gains are large at small size, but diminish sharply if firm size increases.

2.2 Market structure and dynamic entry-exit selection.

In a competitive industry with a homogeneous product there is a direct link between productivity, profitability and firm growth. Profits are zero for the average firm that can just recover its marginal costs from the market price. In such an industry, firms cannot survive and grow when their productivity is substantially less than the average for their industry. The persistence of inefficiencies in a dynamic perspective would be difficult to understand in an industry with a homogeneous product. Unexploited scale advantages could exist only temporarily, because competition would force inefficient firms out of business. Due to replicator dynamics, firms with sub-average productivity would experience ever-decreasing market shares until their size drops below the minimum-efficient size threshold and they exit business (Cantner

2007). Several authors found empirical evidence for dynamic productivity-related selection effects (Foster *et al*. 1998; Brown *et al.* 2006). Jovanovic (1982) developed a framework of 'noisy selection' in which firms have different initial efficiency endowments, and their survival depends on market conditions. Efficient firms grow and survive, while inefficient firms decline and fail. Also Olley *et al*. (1996) deal with endogenous exit behaviour and input choice decisions of firms. The implication of entry-exit selection is that firms with a productivity disadvantage compared to the industry's productivity frontier will not be represented in the long-term 'steady-state' firm distribution (De Wit 2005). Due to the selection effect, large and older firms tend to have a higher productivity than newcomers.

The situation changes once we consider services produced under monopolistic competition where product and market differentiation prevail. Dixit-Stiglitz (1977) modelled such a market form where all firms have a fixed set-up cost and constant marginal costs. If each firm can offer its service variety in its own market niche, the firms will not outcompete each other. If the consumers have a sufficient taste for variety, not all scale effects will be fully exhausted in this Dixit-Stiglitz world. The sole remaining disciplinary market force is the actual or potential entry of new competitors whose product variety competes for the same consumer budget. Given sufficient entry, the market share of each service variety will be spread so thinly that the most inefficient producers can no longer recover their marginal cost and drop out. If free entry in a monopolistic services market is restricted, relatively inefficient producers may survive in the market. Both in static and dynamic terms, this lowers productivity performance.

Finally, competition intensity and productivity selection may also be hampered through market power of incumbents and a lack of foreign competition. The lack of incentives or competitive pressures may lead monopolistic firms to neglect minimizing unit costs of production, i.e., to tolerate "X-inefficiency" (Caves *et al.* 1975). A lack of international openness of services markets prevents the exposure of inefficient firms to the productive and innovative foreign challengers. In that respect, the integration of European markets for services still has a long way to go (Copenhagen Economics 2005; Kox *et al.* 2004, 2006). The business services branches IT consultancy, equipment renting and personnel recruitment are the most exposed to foreign competition, while the most sheltered branches are accountancy and tax consultancy (CSES 2001).

If firms over time persistently underperform in productivity in European business services, this either indicates that imperfect competition prevails, or that the industry has not yet arrived in a steady-state. Maybe Vernon's concept of industry life cycles deserves another look, as some branches of the business services industry only came into existence over the last 15 years. Vernon (1966) notes that early in the industry life cycle it is normal that markets, products and production methods display great diversity, and that producers and consumers are not (yet) geared towards price competition or cost efficiency.

2.3 Regulatory barriers and productivity performance.

Reviewing recent theoretical literature on the relationship between entry, exit and productivity, Kocsis *et al.* (2009) conclude that actual or potential entry does encourage at least some of the incumbents to become more efficient. Entry is driven by market opportunities arising either exogenously from GDP growth or as a result of the entrant's own efforts like e.g. innovation activities. Market-entry barriers may however discourage or even deter entry. Lowering the size of regulatory entry barriers can thus indirectly stimulate higher productivity, because it strengthens competition and/or innovation.

Service markets have a long history of regulation, caused by market failures like externalities and information asymmetry that may play a role in the production, distribution and consumption of services. Because the production and consumption of the service products often cannot be separated in place and time, services products are difficult to standardise, so that the quality of the services product is a priori uncertain for the consumer. The buyer of complex professional and medical services is often confronted with a structural information asymmetry. The latter forms a basic motivation for much of the regulations in professional and business services.

Product market regulation in professional business services may create obstacles to new firm entry in the market and it can have a decelerating effect on the process of market share reallocation from less efficient to more efficient firms (Nicoletti *et al*. 2003; Djankov 2002). The impact of regulation can be such that it introduces fixed entry costs for new firms and thus effectively protects incumbent firms. Especially knowledge-intensive services are subject to several types of national regulatory measures (Copenhagen Economics 2005; Kox *et al*. 2006; Paterson *et al.* 2003).

Regulatory burdens that do not discriminate between firm size often result in a disproportionately large compliance costs impact for small and medium-sized firms, hindering their post-entry growth (Paterson *et al.* 2003; Baker *et al.* 2008). Bartelsman *et al.* (2000) note that while entry and exit rates are fairly similar across industrial countries, post-entry performance differs noticeably between Europe and the United States. Post-entry growth in the EU is on average much slower in the EU and regulatory differences might partly explain this difference. Klapper *et al*. (2006) show that European countries with more costly entry regulations experience a slower growth of firms numbers in industries with high entry than the US. Costly regulations hamper the creation of new firms, force new entrants to be larger and cause incumbent firms in otherwise high-entry industries to grow more slowly. Baker *et al.* (2008) conclude that the impact of stringent regulations regarding the types of activities that services providers are allowed to offer are reflected in the levels of concentration and consolidation observed in national markets. They find that in security services and temporary employment services, countries with high levels of national regulation are characterised by much higher degrees of market concentration. By contrast, stringent national regulations on who can perform technical consulting services in some EU member states appear to have the opposite effect, by creating an entry barrier to these national markets for international competitors and restraining the development of larger companies. Olley *et al.* (1996) estimate firm's exit and investment behaviour in the telecommunications equipment industry during stages of deregulation in the 1960s, 1970s, and 1980s and find that the deregulation waves went along with considerable intra-industry resource reallocation. The breakdown of entry barriers apparently altered choices of producers and potential producers regarding their input choices, innovative activity, and production volumes. Eventually this results in higher productivity growth through a reallocation of market shares, shift in vertical production chains, and an enlarged field of competitors.

Not only product-market regulation, but also regulatory measures for employment with regard to labour turnover and employment may affect the resource allocation and productivity performance of firms. Gust *et al.* (2002) develop a model with vintage capital and labour to evaluate the effect of more stringent labour market regulations on a firm's decision to adopt new technologies. They analyse that a tax on firing workers delays the adoption of information technology (IT) when technological change is skill-biased and when firms can only upgrade the quality of their workforce through labour turnover. If IT technology adoption is delayed, this lowers productivity. Their empirical results are largely consistent with their model.

Finally, several authors show that stringent regulation in services may have knock-on effects in the rest of the economy. Rajan *et al*. (1998) found that better efficiency in financial services reduces the costs of external finance to firms. Barone *et al.* (2008) have established that a similar mechanism operates in the professional services industry and this affects the use of such services by manufacturing industry. In countries with lower service regulation they find faster growth in value added, productivity, and exports by downstream service-intensive industries. While they focus on the effects of anti-competitive service regulation, their estimates appear robust for considering alternative forms of regulation such as product and labour market regulation.

Summarising, the literature review mentions three structural factors that may hamper productivity performance of a services: scale ineffciencies, market dynamics and regulatory factors. All three elements will be taken into account in the model that we will be testing.

3. Empirical strategy

We identify a productivity frontier in EU business services, distinguishing between sub-sectors, countries and size classes. We use two empirical models: a global stochastic frontier model (GSF) with deterministic features, and a non-parametric data-envelopment model (DEA). The parametric and non-parametric model have different strengths and weaknesses, hence we will show the results of both approaches. Once having identified the productivity frontier we test whether the incidence of sub-frontier productivities by size class is explained by X-inefficiencies. Next, we investigate the impact of market and regulatory characteristics on the pattern of scale inefficiencies.

We apply the GSF model to analyse scale economies and efficiency frontiers (e.g. Khumbakar *et al.* 1991). The GSF model is built around a translog production function that enables us to identify nonlinearities in the response of output to the scale of some inputs. The model identifies a parametric productivity frontier that is fixed by the estimated technology parameters of the translog production function in combination with the minimal quantities of each input. The GSF model simultaneously identifies the productivity frontier and explains X-inefficiency in terms of market and regulatory variables.

The GSF model assumes that frontier productivity may differ between size, country and sector. However, the technology parameters of the frontier model are identical for all observations. This method would be inappropriate if the production elasticities are not constant across sub-sectors or the entire size range, e.g. in case of technological or organisational discontinuities across the size range. To deal with this possibility we apply a robustness analysis with a model that uses inefficiencies derived from Data Envelopment Analysis (DEA). The DEA-model allows more flexibility by dropping the homogeneity assumption underlying the parametrically defined frontier allowing a deeper look into the nature of the scale effects.

3.1 GSF model.

The availability of panel data enables us to apply the global stochastic frontier model of Battese and Coelli (1995) based on a technical production function of the translog type. The translog specification allows for inputs to have an effect on output that can vary with the output level. It explicitly checks for local scale effects by adding quadratic terms and interaction terms for the inputs.

The starting point is a value-added production function, because this does not need restrictive separability assumptions on the underlying technology (Diewert 2005; Schreyer 2001). The Battese-Coelli model imposes that the error term of the translog model consists of deterministic X-inefficiencies τ, and a white-noise component μ. A second equation explains the X-inefficiencies (τ) from a vector of exogenous variables. After rewriting the translog product function to get labour productivity as the dependent variable, the two-equation GSF model reads:

$$\ln\left(\frac{Y_{it}}{L_{it}}\right) = \lambda_L + \beta_1 \ln K_{it} + (\beta_2 - 1)\ln L_{it} + \frac{1}{2}\beta_{11}(\ln K_{it})^2 + \frac{1}{2}\beta_{22}(\ln L_{it})^2 + \beta_{12}(\ln K_{it} \times \ln L_{it}) + \sum_r \alpha_r \mathbf{B}_{it} + \mu_{it} - \tau_{it} \quad (1)$$

$$\tau_{it} = \gamma' \mathbf{Z}_{it} + \theta_{it}. \quad (2)$$

In (1) Y is value added, K denotes physical capital inputs, and L represents labour inputs. The parameters β_1 and β_2 reflect the linear effects of more inputs on value added. The parameters β_{11} and β_{22} represent the non-linear input effects. The 'cross' parameter β_{12} picks up local interactions between capital and labour; it becomes significant if the output elasticity of a particular input depends on the level of the other input (input complementarity). Vector **B** in the first equation collects a set of dummy variables to control for unobservable frontier productivity differences between sub-sectors, countries, size classes and time. Furthermore, subscript t refers to time and subscript i denotes a panel indicator that refers to a particular combination of country, sub-sector and size class. Equation (2) reflects that mean X-inefficiencies (τ) are determined by the exogenous variables collected in **Z** and that deviations from these means are random ('white noise'), represented by θ. **Z** may include variables linked market structure and regulatory environment, as will be specified later on. The random variable θ is defined by the truncation of the normal distribution with zero mean and variance σ_τ^2, such that $-\gamma'\mathbf{Z}_{it}$ is the point of truncation.[2] Hence, $\theta_{it} \geq -\gamma'\mathbf{Z}_{it}$.

The GSF panel data method of Battese and Coelli (1995) boils down to parametrising the deviations from frontier productivity by using equation (2) and by estimating the two equations simultaneously with a Maximum Likelihood method. Our application of the Battese-Coelli model assumes the following:

- A homogeneous technology holds for all countries, sub-sectors, size classes and years, so that technology parameters are equal for all firms.
- Frontier productivity can differ by firm size, country, sub-sector and year (identified by the dummies collected in **B** in equation (1)).
- Firms can under-perform compared to the frontier and this under-performance depends in a deterministic way on the variables collected in the **Z** vector.
- Size-related X-inefficiencies are estimated after controlling for exogenous market structure variables and regulation variables.

3.2 DEA model.

A parametric model like the GSF model may cope with the stochastic nature of the relation between output and inputs. In the absence of knowledge of the underlying production process, the translog technology as assumed in the GSF model may be a good first representation. The GSF model imposes the assumptions that all size classes can apply the same technology and that scale effects occur over the entire scale range. Although flexible, the GSF model imposes a restrictive functional form and it needs specific assumptions concerning the distribution of efficiencies. Moreover, our GSF estimates may suffer from endogeneity or simultaneity biases when a correlation exists between the inputs and the disturbance term of the production function. Zellner *et al.* (1966) pointed out that capital and labour inputs are not correlated with the disturbance term of the production function if we are willing to assume that the underlying full model takes 'expected' and stochastic output and 'expected' and stochastic profit maximization as the starting point.[3]

The fitted GSF technology is an "average" or sample-wide estimate, which may not represent scale behaviour at lower levels. The GSF model is adequate to detect sample-wide scale effects under the assumption that firms in all scale classes apply the same technology. This is a good approximation if we do have insufficient knowledge about the firm's production process. GSF thus yields an "average" sample-wide result. The GSF model is less appropriate when we expect that technology may differ across firm size.

[2] These assumptions are consistent with θ_{it} being a non-negative truncation of the $N(\gamma' Z_{it}, \sigma_\tau^2)$ distribution which is assumed not be correlated with the idiosyncratic disturbance μ_{it} of equation (1).

[3] Annex 1 demonstrates that this type of endogeneity is probably of limited relevance in the present study.

The translog estimates may suggest the presence of constant returns to scale (CRS), whereas we have in reality variable returns to scale (VRS). Even if the CRS assumption is not rejected for the entire sample by the translog estimates, still many firms could operate on a sub-optimal scale. Moreover, a firm that is operating on the technological frontier may not be as productive as the frontier firms in other size classes if scale efficiencies differ locally by size class. Because of these issues we apply the Data Envelopment Analysis (DEA) as a robustness check and as an alternative for investigating the interaction between scale effects and market structure. The DEA method does not impose an a priori structure on productivity relations of interest, whereas in the GSF model the efficiency estimates are directly related to the model parameters (assumed to be unbiased).

The DEA method proceeds by applying linear programming to construct a non-parametric piece-wise surface over the observed data for each meaningful grouping of firms (e.g. Coelli *et al*. 2005). This gives a technological frontier that represents the 'best-practice' technology. From this we subsequently derive a set of X-efficiency measures and a direct measure of scale efficiency by size class. This approach circumvents the technological homogeneity assumption of the parametric GSF approach. It also avoids the potential simultaneity biases related to the estimated parameters for the translog model.

3.3 Implementation of DEA and calculation of scale inefficiency

A few choices have to be made for implementing DEA. We assume that firms have a better control over their inputs than over their output, and hence we follow the input orientation. DEA with input orientation looks at the potential cost reductions that can be achieved given a certain level of output. A second 'fine tuning' is that we allow both for a variable-returns-to-scale (VRTS) technology and a constant-returns-to-scale (CRTS) technology.

We construct for every business services branch (*j*) and each year (*t*) a 'model free' global efficiency frontier by pooling data of all size classes and countries in our sample. This allows us to calculate an X-efficiency indicator, based on the distance to the global industry-specific frontier for each combination *i* of country and size class.[4] Using *H* as symbol for (average) productivity the VRTS X-efficiency indicator reads:

$$XE_{ijt}^{VRTS} \equiv \left[\frac{H_{ijt}}{H_{jt}^{frontier,VRTS}} \right] \quad ; \; 0 < XE_{ijt}^{VRTS} \leq 1 \,(frontier) \tag{3}$$

[4] Throughout this paper we uniformly use a positive efficiency measure (X-efficiency and scale efficiency) rather than the corresponding negative expression (X-inefficiency, scale inefficiency). Since all our efficiency measures are scaled continuously in the {0, 1} dimension, the corresponding inefficiency measures are simply derived as complements (1 minus the efficiency level).

DEA also allows calculating straightforwardly a direct measure for scale efficiency. This is done by recalculating the size-specific distances to the industry-specific frontiers under the hypothetical assumption that firms operate at an optimal scale under an industry-specific CRTS technology. This yields the counterfactual benchmark for scale efficiency. If a particular size class is the optimal scale the X-efficiency indicator for that size class is identical for the CRTS and the VRTS assumptions. However, if firms size is larger or smaller than the optimal scale, X-efficiencies will be smaller (closer to 0) for VRTS than for CRTS. Using the CRTS efficiency as benchmark the *SCE* scale-efficiency indicator is thus derived as:

$$SCE_{ijt} \equiv \frac{XE_{ijt}^{CRTS}}{XE_{ijt}^{VRTS}} = \left[\frac{H_{ijt} \times H_{jt}^{frontier,VRTS}}{H_{ijt} \times H_{jt}^{frontier,CRTS}} \right] \quad ; 0 < SCE_{ijt} \leq 1\,(frontier) \qquad (4)$$

Summarising, for each grouping of the data we get three efficiency measures: (a) two X-efficiency indicators (XE^{VRTS}, XE^{CRTS}) that depict the distance to the industry frontier (across size classes and countries), and (b) a scale-efficiency indicator that measures per industry the distance of a particular size class to the most efficient size class (across countries). All three efficiency indicators are strictly positive and run from zero (lowest) to 1 (frontier).

Finally, we test whether the X-efficiency scores $XE_{ijt}^{VRTS}, XE_{ijt}^{CRTS}$ and scale efficiency scores SCE_{ijt} can be explained with the help of a panel-data Tobit regression model using as independent variables size class, market characteristics and national regulatory conditions. The structure of the Tobit model for the logarithm of SCE_{ijt} is:

$$\ln(SCE_{ijt}) = \delta'\mathbf{X}_{ijt} + \lambda'\mathbf{Z}_{ijt} + \upsilon_{ijt} \qquad (5)$$

with **X** representing a vector of dummy variables for industries and size classes and **Z** collecting the same market-structure and regulation variables as used in the GSF model. The structure of the Tobit models for the two X-efficiency measures is similar. Based on the literature, we expect a negative impact of regulation intensity on both X-efficiency and on scale efficiency, whereas variables that depict an increase in competition and entry-exit selection are expected to have a positive impact.

4. Data and descriptive statistics

4.1 Introduction

Testing structural productivity determinants (market structure, regulation and scale economies) in the dynamic setting of competitive selection requires firm-level panel data. We need enough inter-country variation to test for the role of regulatory characteristics and we need sufficient data for the smallest firm-size classes to investigate the role of scale economies. The last condition turned out to be a problem. Though nowadays commercial databases are available with data on business services firms in many countries, the representation of small firms in these data sets can at best be called poor. Such data are still only available on a national basis from local statistical authorities, often under strict confidentiality conditions.

We solve the limited data availability by using Eurostat’s NewCronos firm demography database. The available data on business services are sourced from national statistical offices, and cover many EU countries and the period 1995-2005. Each data cell provides information about a *country x industry x size class* combination: the number of firms, total sales, total value added, number of employed persons, and total fixed capital, approximated with depreciation. With these data we *construct* a representative firm or decision-making unit (DMU) for every combination of *country x industry x size class*. Recent empirical insights on the structure of firm size distributions suggest that the firm-size distribution across and within size classes is similar (Axtell 2001). From this we infer that the use of constructed representative firms per data cell still allows marginal analysis as is necessary for the study of scale economies. Annex I addresses this issue in more detail.

The construction of the data base requires a few further decisions, because the national statistical offices until recently used to deliver statistical data on business services industry with different degrees of sector and firm-size detail. To allow full comparison across European countries we homogenise classifications at the lowest common denominator, thus sacrificing some available sub-sector and size-class detail and data years in the data from some countries.[5] Homogenisation across countries yields a fully comparable set of data on business services industry in 13 EU countries, for eight sub-sectors and five size classes for the period 2000-2005.

4.2 Variables

This subsection discusses the sources and the definition of our dependent variable and the explanatory variables respectively that we use for estimating the GSF model and DEA model.

As the central productivity measure and dependent variable for this study we use labour productivity, defined as value added per employed full-time person. The data would have allowed using total factor productivity (TFP) instead, but we have deliberately chosen not to use this measure. TFP is a non-explained residual from growth accounting, and as such a "measure of our ignorance" as Abramovitz already remarked in 1956. For TFP to be a correct measure of multi-factor productivity, a number of crucial conditions have to be met. One of such conditions is that factor input markets and output markets have perfect competition, so that production factors are rewarded according to their marginal product and output prices are equal to marginal costs. Since these market conditions are precisely what we intend to investigate in business services, the use of TFP as productivity measure has to be ruled out.

[5] The firm size classification is derived from the number of employed persons per firm, including employer. We use one employed person per firm as the cut-off point, although some countries offer data for the size class with less than one full-time employed person.

Regarding production technology, we use depreciation as proxy for fixed-capital inputs and for the number of employed persons as proxy for labour input. Both variables come from Eurostat's NewCronos firm demography database.

In order to characterise market structure, a combination is used of three indicators: average market size per firm, the Hirschmann-Herfindahl index (HHI) for concentration of market shares, and the average entry-exit rate per market. The average market size per firm is an indicator for competition intensity. It is calculated as the reciproque of the number of firms per data cell (country X industry X firm-size class), normalised for country size (country's total number of firms in a particular industry). Normalisation is applied to prevent that this variable picks up the effect of country size. The average entry-exit rate per market is an indicator for the intensity of competitive selection. It is calculated as the annual firm births minus annual firm death as a percentage of the number of active incumbent firms by country, industry and size class. Data for these indicators are derived from the Eurostat SBS panel and the Eurostat data on business demography.

Finally, the national regulatory environment of business services firms is depicted by a combination of four indicators, all derived from the World Bank's Cost of Doing Business database. The World Bank data capture both the relative strictness of the regulations themselves as well as the efficiency of the national regulatory apparatus that implements the data.[6] The four indicators are: (a) an overall index based on 28 sub-indices for policy-caused business costs; (b) an exit-costs indicator for the regulation-caused costs of closing a business; (c) an indicator for the costs of setting up a registering a new firm; and (d) an indicator for the degree of inflexibility in employment contracts, representing national differences in costs for labour reallocation, hiring and firing. For each of these for indicators it holds that a higher score represents more regulation-caused costs for firms.

4.3 Descriptive statistics

Figure 1 shows that the size-class dimension of the data set contains variation. The two top curves in the graph depict the average labour productivity per size class in EU business services for the years 2000 and 2005. The curvature suggests that the labour productivity is highest in the size class with 50-249 employed persons. The difference between both curves suggests that average productivity has fallen between 2000 and 2005. The bottom curve in Figure 1 gives the first difference of average productivity by size class, suggesting that average productivity has diminished the least in the size class with 10-19 employed persons. The graph only gives a first description, without correction for fixed-capital intensity or for composition differences (industry, country) in the averages for both years.

[6] This database shows national differences in policy-related costs of doing business by quantifying per country how identical, well-defined business plans would be handled by national regulatory systems in terms of costs, time efficiency and red tape (cf. Djankov et al. 2008). For a full description of the case studies see www.doingbusiness.org. While the Costs of Doing Business database only provides national rankings, we have use the database to derive more precise indicators for a number of sub-aggregates of business costs. The calculation method of the indices is documented in the Annex of Nordås et al. (2009).

Figure 1 Average labour productivity by size class in total EU business services, average for 13 EU countries, 2000 and 2005

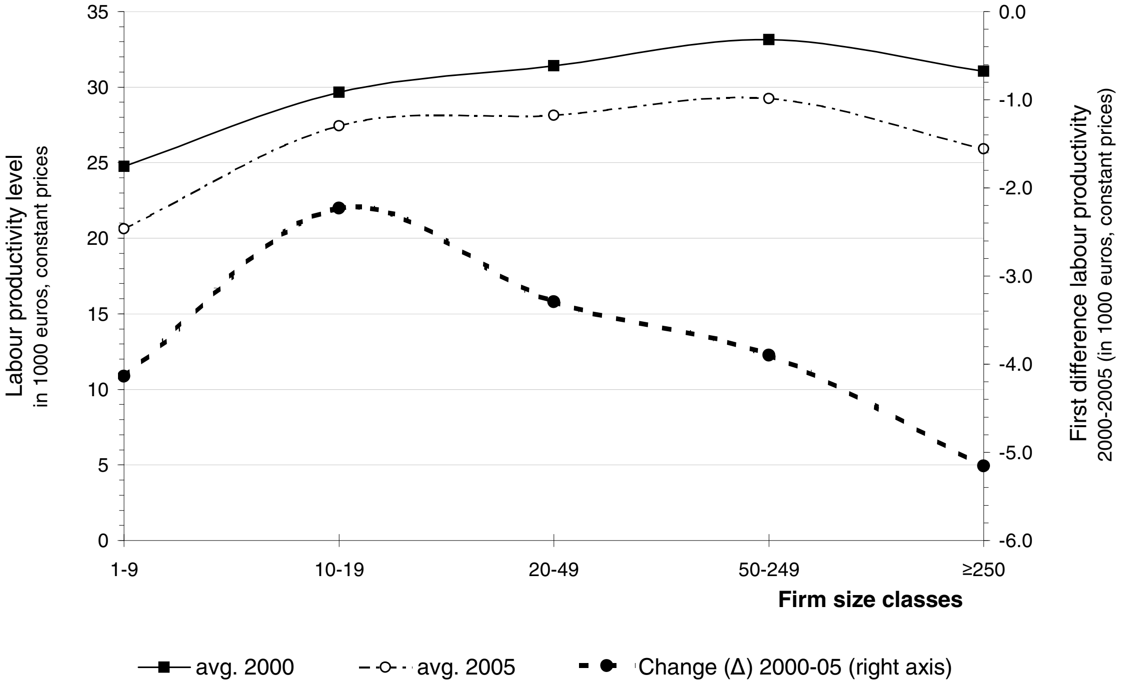


Table 1 Selected country characteristics of the dataset, all industries, 2000-2005

Country	No. of data points	No. of firms covered (x1000)	Employ-ment covered (x1000)	Product-ivity level [a] (x1000 euro)	2000 -2005 average share (%) of small firms[b] in: total no. of firms	total employ-ment	Overall cost of doing business [d] 2005	Cost of starting up a new firm [e] 2005	Flexibility in employment contracts index [f] 2005
Austria	196	42	243	28.4	91.3	35.6	0.76	0.61	0.69
Belgium	184	76	386	33.8	95.7	28.5	0.69	0.61	0.62
Denmark	96	16	108	37.6	91.4	24.6	0.55	0.19	0.20
Finland	98	16	81	33.2	94.1	33.6	0.67	0.25	1.09
France	240	399	2684	29.7	93.5	24.2	0.79	0.26	1.40
Germany	240	344	3242	28.6	87.0	23.0	0.84	0.60	1.34
Ireland	103	11	70	34.4	91.5	36.4	0.65	0.38	0.50
Italy	240	739	2059	28.0	97.5	53.0	1.08	0.66	0.83
Netherlands	230	104	677	42.1	91.7	24.8	0.80	0.53	1.02
Portugal	193	60	281	12.6	96.2	37.0	1.12	1.06	1.56
Spain	160	378	1918	18.9	95.2	34.7	1.12	1.01	1.54
Sweden	207	141	453	30.4	96.7	43.2	0.80	0.25	0.96
Un.Kingdom	175	426	3234	44.0	91.2	26.8	0.44	0.34	0.29
Total	2362	2751	15436						
Average	182	212	1187	30.9	93.3	30.9	0.79	0.52	0.93

a) Productivity level as value added per employed person (in 1000 Euros, constant prices), average for all business services branches, 2000-2005. b) Share of firms with less than 10 employed persons. c) Composite indicator of regulation-caused cost of doing business (0 is lowest level), relative to a 60-country sample, based on 28 subindicators in Cost of Doing Business database (cf. Nordås *et al*. 2009). d) Relative regulation-related costs of starting up a new firm (0 is lowest level), relative to a 60-country sample, based on 3 subindicators in Cost of Doing Business database (cf. Djankov et al. 2002; OECD 2009). e) Composite indicator for regulation-related flexibility in hiring and firing workers (0 is lowest level), relative to a 60-country sample, based on 4 subindicators in Cost of Doing Business database (cf. Nordås *et al*. 2009).
Data sources: Eurostat New Cronos, Firm demography, business services by size class. Data for the Netherlands compiled from the production census data of Statistics Netherlands, using the New Cronos classification of size classes. Regulation indicators derived from World Bank Cost of Doing Business database (for calculation method, see: OECD 2009).

Table 1 presents descriptive statistics on the country variation in the data set. With on average 182 data cells per country we have 2,362 observations, covering 2.8 million EU business services firms with 15.4 million employed persons. The latter numbers show that business services typically forms a small-scale industry. The overwhelming share of firms has less than ten employed persons. Italy, Portugal and Sweden have the largest share of firms with less than ten employed persons. In terms of their share in total employment, the smallest size class accounts inmost countries for 25-33% with again Italy and Sweden being the exceptions. The average productivity differs considerably between countries, though industry composition effects and country differences in average income also play a role here. Average productivity is highest in Netherlands and the UK, and lowest in Italy and Portugal.

Table 1 also displays country differences with respect to three regulatory variables that we will use as explanatory variables. The three regulation indicators show considerable variation between countries.

The average productivity level in many branches of business services is quite high compared to manufacturing. Knowledge-intensive services firms have a higher value added per worker because they employ highly qualified workers with relatively high wage rates. Productivity levels are much lower in business services sectors that produce standardised services like industrial cleaning, security, packaging, bookkeeping and administrative tasks. In Table 2 we document the variation in our dataset by the industry dimension, showing that substantial differences exist between the 3-digit sub-sectors. Productivity levels

Table 2 Selected industry characteristics of the dataset, average for 13 EU countries, 2000-2005

Industry branch by NACE code [a)]	No. of data points, annually	No. of firms covered annually (x1000)	Employ-ment covered annually (x1000)	Produc-tivity level (x1000 euro) [b)]	Average firm size (in empl. persons)	Average fixed capital per employed person [c)]	Average entry-exit rate [d)]	Average market share concentra-tion (HHI-index) [e)]	Average market size per firm [f)]
K720	245	335	1952	49.3	5.8	35.5	4.7%	0.114	0.02%
K741	309	937	3363	38.9	3.6	32.3	4.2%	0.137	0.02%
K742_3	365	591	1975	35.8	3.3	29.0	2.5%	0.132	0.04%
K744	270	123	610	34.2	5.0	26.6	2.3%	0.128	0.07%
K745	293	30	2014	25.5	66.2	5.7	7.8%	0.129	0.06%
K746	278	21	594	19.0	28.2	11.1	5.1%	0.130	0.13%
K747	305	101	2183	14.6	21.6	7.6	3.0%	0.129	0.04%
K748	297	403	1504	29.6	3.7	34.8	4.7%	0.130	0.04%
Total	2362	2542	14194						
Average				30.9	17.2	22.820	4.3%	0.129	0.05%

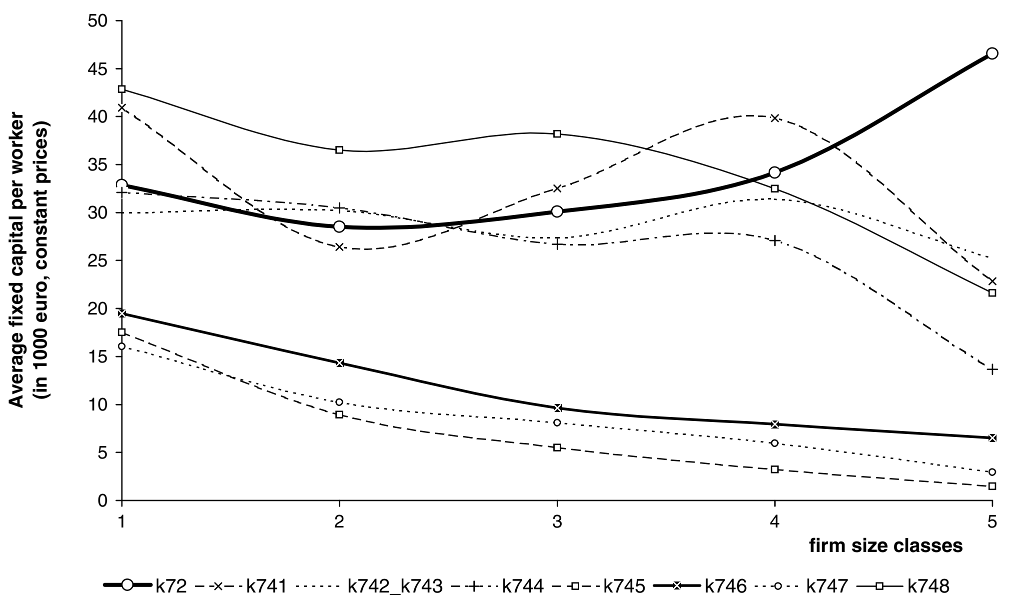
a) Codes: K720 = computer-related services; K741= Legal, accounting, and auditing activities; tax consultancy; market and public opinion research ; business and management consultancy; K742_3 = Engineering, technical testing, architects; K744 = Advertising; K745 = Labour recruitment and (temporary) provision of personnel; K746 = Security services and investigations; K747 = Industrial cleaning; K748 = Miscellaneous business activities not elsewhere classified. b) Productivity level as value added per employed person (in 1000 Euros, constant prices), average for all sample countries, 2000-2005. c) Firm average for fixed capital per employed worker (in 1000 Euros, constant prices), average for all sample countries, 2000-2005. d) Average entry-exit rate: annual firm births minus annual firm death as a percentage of the number of active incumbent firms. e) Hirschmann-Herfindahl market concentration index. f) Industry average for market share per firm (normalised by total number of firms per country), average for all sample countries, 2000-2005. Data sources: own calculations based on Eurostat NewCronos data, SBS and EUKLEMS data.

are highest in K720 (computer services) and K741 (legal, accounting, and consultancy services). The sub-sectors K745 (temporary labour intermediation), K746 (industrial cleaning) and K747 (security services) display a distinctly larger average firm size than the rest of the sub-sectors. This difference in apparent scale economies is mirrored in a significantly lower amount of fixed capital per worker between these three sub-sectors and the rest of them.

Table 2 also shows average differences with regard to three indicators for market structure. Sub-sectors K745 and K746 have above average entry-exit rates (relatively strong dynamic selection), while K742/3 (engineering and architectural services) and K744 (marketing services) have low entry-exit rates (i.e. sluggish selection dynamics).

Figure 2 plots fixed-capital intensity per worker for the five different size classes. This confirms the indications from Table 2 about the differences in apparent scale economies between sub-sectors. The fixed-capital economies are about exhausted at a scale of 50 employed persons in temporary labour, cleaning and security services, whereas the picture in other branches is much more differentiated. The computer services industry displays an U-shaped capital intensity, which is markedly different from all other industries where the largest size class has the lowest capital intensity. A possible explanation for the pattern in computer services is that the largest size classes invest more in basic research and mainframe systems per employee.

Figure 2 Capital intensity per employed worker, 2000-2005 average by industry



Note: industry codes are: K72 = computer-related services; K741= Legal, accounting, and auditing activities; tax consultancy; market and public opinion research ; business and management consultancy; K742_43 = Engineering, technical testing, architects; K744 = Advertising; K745 = Labour recruitment and (temporary) provision of personnel; K746 = Security services and investigations; K747 = Industrial cleaning; K748 = Miscellaneous business activities not elsewhere classified.

5. Estimation results

5.1 Results GSF-model

Table 3 presents the estimates of the GSF model. Panel A shows the results of equation (1). Business services firms are – on average – characterized by increasing returns to scale, because the sum of the estimated technology parameters is slightly above one. The parameters for the non-linear input effects of the technology variables are significantly different from zero, indicating that scale effects are local and depend on input size. Note that the results are obtained after controlling for frontier differences through dummies for countries, sub-sectors and size classes.

Table 3 Estimates General Stochastic Frontier (GSF) model, panel data 2000-2005

	Dependent variable: log(labour productivity)	
	Estimate [a)]	t-value
A) Translog-derived production function		
Technology variables:		
* Fixed capital	0.23***	11.3
* Labour inputs	0.92***	18.5
* Capital based local scale effects	− 0.05***	− 5.1
* Labour based local scale effects	− 0.12***	− 11.7
* Capital-labour interaction	0.05***	6.8
Industry dummy included	yes	
Country dummy included	yes	
Size dummy included	yes	
Year dummy included	yes	
Constant	3.18***	56.8
B) X-inefficiency equation		
Market structure variables:		
* Average market share per data cell	− 0.04***	− 4.0
* HHI, Herfindahl index, micro-based	− 0.23	− 0.5
Regulatory environment:		
* Overall Cost of Doing Business indicator	1.41***	6.6
Size dummies included	yes	
No. of observations	2362	
Log Likelihood	366.6	
a) Codes: * significant at 10% confidence level, ** significant 5% level, *** significant at 1% level.		

Panel B of Table 3 presents the simultaneous estimates for equation (2) of the GSF model. For the interpretation of these results it is important to realise that panel B gives the results for equation (2) in which τ is an X-inefficiency measure. So a positive parameter sign means that the variable contributes positively to the degree of inefficiency, and hence lowers efficiency. The estimates suggest that a larger average market share (i.e., less firms per data cell) increases X-efficiency. This effect is counter-intuitive. A possible explanation is that this result picks up a positive correlation between average market share and scale efficiency. Arguably, in order to be able to capture scale economies firms have to grow, and gaining market share is a way to achieve this. This result may therefore point to the endogeneity of market shares.[7] Fiercer competition may force inefficient firms to leave the market. This increases the market share of efficient firms, and positively correlates with X-efficiency. Next, market concentration as measured by the HHI appears not to have a significant impact on X-efficiency. Finally, higher regulation intensity according to 'Cost of Doing Business' indicator has a significant negative effect on X-efficiency. This indicator is lagged one year which we assume to be a reasonable reaction time for firms. An explanation for this is that incumbent firms become less efficient as the threat of entry is lower due to more regulation related with sunk costs. This is in line with the predictions from the literature (cf. section 2).

5.2 Comparison with DEA

We apply DEA both as a robustness check on the GSF results and as a method that allows to look deeper into the issue of scale efficiency. As can be seen in equation (4) the scale-efficiency indicator depends on both X-efficiency indicators (XE^{VRTS}, XE^{CRTS}). Inaccuracy would occur when measurement error hinders the correct identification of the VRTS and CRTS reference points for a particular data cell or *decision-making unit*. Annex I explains why this type of bias will be limited given the type of data that we use.

Table 4 compares the X-efficiency predictions of the GSF method with the X-efficiency measures derived from DEA (XE^{VRTS}, XE^{CRTS}). We recall that the DEA measures are calculated for every services sub-sector and year. The size of the XE^{VRTS} results is similar to the GSF-predictions for the smallest

Table 4 Comparison of GSF and DEA X-efficiencies, averages per size class, 2000-2005

	Predicted efficiency GSF-model [a)]	Calculated X-efficiencies on basis of DEA-model [b)]	
	(median for size class)	XE^{VRTS} (median for size class)	XE^{CRTS} (median for size class)
Size classes:			
* 1–9 employed persons	0.857	0.924	0.417
* 10–19 employed persons	0.870	0.605	0.566
* 20–49 employed persons	0.907	0.620	0.599
* 50–249 employed persons	0.883	0.668	0.653
* ≥250 employed persons	0.819	0.808	0.701
All size classes	0.875	0.722	0.594

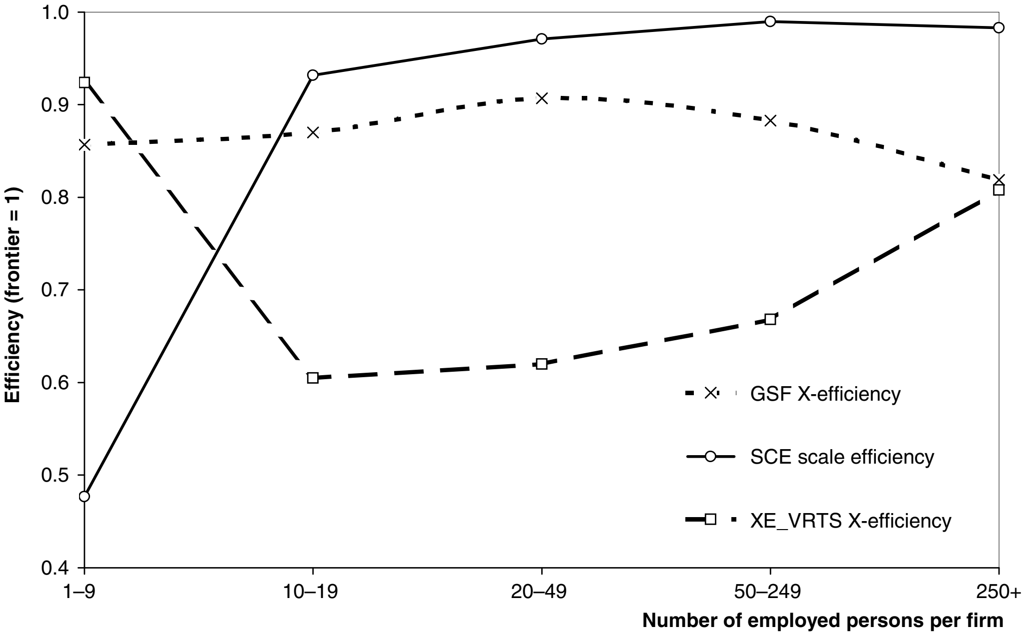
a) X-inefficiency predictions on the basis of Battese-Coelli method calculated as $e^{-\tau}$ in order to be comparable with the DEA indicators.
b) X-inefficiency indicator DEA allowing variable returns to scale (cf. equation 3).

[7] The method of Battese and Coelli (1993) does not allow to take endogeneity of regressors into account.

and the largest size classes. However, for the other size classes we find different estimates. This is not surprising, because a non-parametric variable-returns-to-scale frontier always envelops the data more tightly than the returns-to-scale technology embodied in the GSF model. Averaged over all observations, the GSF model overestimates the X-efficiency in comparison to the preferred XE^{VRTS} measure, while the XE^{CRTS} indicator tends to underestimate it.

The DEA X-efficiency indicators give the distance to an industry-wide frontier averaged across all size classes. It is however possible that not all size classes have the same efficiency, some may be operating on a sub-optimal scale, not exhausting potential scale gains. This is measured by the *SCE* scale-efficiency indicator (equation 5). We have jointly pictured the three most relevant efficiency indicators in Figure 3. The results are quite spectacular. The smallest size class has the lowest degree of X-inefficiency according to XE^{VRTS} (and about the GSF average). It means that *within* this size class firms apply nearly

Figure 3 Comparison of three efficiency indicators by size class (average all sub-sectors and countries, 2000-2005)



similar technologies. However, the SCE scale-efficiency indicator shows that -from a productivity perspective- the technology of the smallest size class is definitely sub-optimal compared to other size classes. The scale efficiency is only about half that of the next size class (10-19 employed persons). Beyond 10-19 workers scale efficiency increases only marginally, reaching a top at 50-249 workers. The average X-efficiency is however lowest in the size classes with 10-49 workers, suggesting that within these size classes there must be the largest dispersion of applied technologies compared to all other size classes.

Firms operating on a sub-optimal scale may fall within the increasing-returns-to-scale part of the production function. We explore this issue by a further analysis of the DEA results. For each data cell we calculate whether it is subject to increasing, decreasing or constant returns to scale (RTS). Whether a data cell is subject to increasing, decreasing or constant returns to scale is calculated by solving a corresponding linear-programming problem for each observation.

Table 5 presents the distribution over size classes of RTS-characteristics and the scale inefficiency scores, averaging over all years, countries and sub-sectors. The vast majority of data cells appears tot operate in the increasing-returns-to-scale region (IRTS) of the production function. The distribution across size classes shows however that also a considerable number of cases operates in the decreasing-returns-to-scale region (DRTS). The pattern of DEA-scale efficiencies permits the conclusion that many small firms have the potential to increase their productivity by a better use of scale economies. Especially the potential scale gains of the smallest firms look quite sizable.

Table 5 DEA scale efficiencies and the nature of marginal returns to scale by size class (average all sub-sectors and countries, 2000-2005)

	Scale-efficiency (***SCE***), median by size class [a)]	Nature of marginal returns to scale, % of cases per size class		
		increasing (IRTS)	decreasing (DRTS)	constant (CRTS)
Size classes:				
* 1–9 employed persons	0.477	97.0	0.6	2.3
* 10–19 employed persons	0.932	85.8	10.7	3.5
* 20–49 employed persons	0.971	80.4	15.0	4.6
* 50–249 employed persons	0.990	64.8	27.5	7.8
* ≥ 250 employed persons	0.983	26.0	55.0	19.0
All size classes	0.955	72.1	21.7	7.1

[a)] Scale-efficiency indicator as defined in equation 4 (using constant returns to scale as a benchmark).

5.3 Explaining DEA inefficiencies

In a fully competitive industry with entry-exit selection it would be difficult to understand why scale inefficiencies could persist over time. The question is to what extent scale efficiencies in the panel dimension can be explained by market-structure and regulation. We analyse this question with a Tobit regression model. Because of our data limitations we cannot identify whether individual firms move between size classes. We therefore opt for a random-effects panel estimator instead of relying on a model with firm-level fixed-effects.[8] We compensate for this data restriction by adding control data on the intensity of entry-exit selection per business services industry and per country from another source (Eurostat Business Demography data).

Whereas in Table 3 we only used one comprehensive indicator for national regulation differences, it is now time to zoom in on the role of specific regulation domains so as to understand which

[8] The data-driven use of 'average' firms per data cell (country X industry X size class) as basic units of analysis limits the range of applicable econometric methods. The availability of full micro data would have allowed to control whether firm-specific fixed effects (such as management quality) are important for the production and input choices that govern productivity outcomes. However, FE testing is out of the question, since we cannot identify which firms are represented in each year's data cell 'average'. A firm that in year t is in size class 1 may or may not have been grown into size class 2 at year t+x.

regulation types matter most for productivity and scale economies. Regulation indices for three specific policy areas are added: the costs of starting up and registering a new business (entry costs), the costs of closing a business (exit costs), and the costs of inflexibility in employment contracts (representing national differences in costs for labour reallocation, hiring and firing).

Table 6 provides the marginal effects of a change in the explanatory variables in the conditional mean for DEA X-efficiencies and DEA scale efficiencies calculated on the basis of the random-effects Tobit models. All continuous variables are expressed in logarithms, so that their estimated parameters can be interpreted as elasticities. All market structure and regulation variables in the columns (1) and (2) have a negative impact on X-efficiency as we would expect them to have. The impact of average market share per firm (within a data cell) does not appear to be statistically significant, however. The regulation-caused entry costs, exit costs and employment inflexibility all have a negative impact on X-efficiency, with the largest effect coming from exit costs.

Table 6 Estimates for DEA efficiencies based on Random Effects Tobit model

	Dependent variables			
	DEA X-efficiencies		**DEA Scale efficiencies**	
	log(XE^{VRTS})		log(SCE)	
	(1)	(2)	(3)	(4)
	Estimated [c]	Z	Estimated [c]	Z
Size-class dummies: [a]				
* 10 - 19 empl. persons	− 0.507***	− 12.5	0.623***	22.3
* 20 - 49 empl. persons	− 0.471***	− 11.2	0.657***	22.7
* 50 - 249 empl. person	− 0.405***	− 9.0	0.655***	21.2
* ≥ 250 empl. persons	− 0.224***	− 4.4	0.562***	16.1
Market structure:				
* Average market share	− 0.005	− 0.9	0.019***	5.1
* HHI (micro based)	− 0.023***	− 3.7	− 0.014***	− 4.0
Regulation indices:				
* Starting a business	− 0.140***	− 6.8	− 0.002	− 0.2
* Closing a business	− 0.211***	− 3.1	− 0.224***	− 5.0
* Employment inflexibility	− 0.067***	− 2.7	− 0.057***	− 3.6
Industry dummies [b]	Yes		Yes	
No. of observations	2362		2362	
Log Likelihood	808.6		479.6	

[a] The smallest size class (1-9 employed persons) is taken as a benchmark. [b] The computer services industry (K720) is taken as a benchmark. [c] Codes, derived from Z values: ** significant at 5% confidence level, *** significant at 1% level. Source: own calculations.

The columns (3) and (4) of Table 6 give the Tobit random-effect estimates for the model that explains DEA scale-efficiencies. Having a higher within-size class market share appears to increase scale efficiency. Like in the GSF estimates our hypothesis to explain this effect is that, in order to capture scale economies, firms have to gain in market shares. The strong impact of scale diseconomies in the smallest size class (as depicted in Figure 3) might be sufficient to explain this effect. This is all the more plausible since the significant negative estimate for the HHI means that over the entire range of size classes a higher entry costs play no role for the large scale inefficiency of the smallest size class (Figure 3).[9] Regulation-related exit costs appear to form the main regulatory obstacle for competitive selection and efficiency, followed only at distance by the regulation-caused employment inflexibility. These two regulation sub-indicators measure different things as appears from the correlation matrix for the applied regulation indicators in Annex 2.[10]

5.4 Adding information on the dynamics of entry and exit

The regulation variables in Table 6 might pick up the intensity of real entry-exit dynamics while regulation itself is not the 'culprit'. As a robustness test we therefore check whether the previous results remain stable after including a measure of real entry-exit dynamics. We include this variable in the Tobit models for DEA scale efficiencies. The results are presented in Table 7.

We find a positive parameter for the entry-exit variable; entry-exit intensity apparently captures an additional competitive incentive separate from competition between incumbent firms. Higher net entry rates increase the incentive to gain in efficiency and this impact on efficiency turns out to be rather considerable.

More striking is the result that adding net entry-exit rates does not alter the other estimates very much. There is no change in significance of the already included variables. Despite the reduction of the sample (from 2362 to 1238), the negative impact of regulation-caused exit costs turns out to be even stronger than before, and the same holds for the negative impact of regulation-caused employment inflexibility. Apparently, both regulation types really obstruct the process of competitive selection in business services, and hence, hinder an improvement of the productivity performance of business services in the EU.

5.5 Testing for optimal scale size

Another feature of our data is that we are able to test for the existence of an optimal scale of operation in business services using the size-class dummies. Their estimated parameters can be interpreted as the difference in scale efficiencies between size classes, conditional on other determinants of (differences in) scale efficiency. The Tobit models of Tables 6 and 7 use a constant term (not reported). Thus the estimates for the size dummies in these tables refer to the difference of size related scale efficiencies compared to the reference group, i.e. the size class with firms employing less than 10 persons (size class 1).

[9] An intuitive interpretation might be that a personal computer and small office are sufficient to startup in many branches of the business services.

[10] Annex 2 shows possible multicollinearity between the sub-indicators 'Starting a Business' and 'Employment Flexibility' (pairwise correlation coefficient of 0.59). However, since 'Starting a business' is not statistically significant in the regressions of Tables 6 and 7 this need not be a problem. The umbrella indicator for Overall Costs of Doing Business correlates strongly with two sub-indicators ('Starting a business', 'Employment Flexibility'), but we do not apply the umbrella indicator jointly with the sub-indicators.

Table 7 DEA scale efficiencies estimated by Random Effects Tobit model after including net entry-exit rates, 2000-2005

	Dependent variables			
	log(***SCE***)		log(***SCE***)	
	panel data		panel data	
	(1)	(2)	(3)	(4)
	Estimated [c]	Z-value	Estimated [c]	Z-value
Size-class dummies: [a]				
* 10 - 19 empl. persons	0.719***	19.3	0.696***	18.7
* 20 - 49 empl. persons	0.755***	19.5	0.723***	18.5
* 50 - 249 empl. person	0.759***	18.2	0.715***	16.9
* ≥ 250 empl. persons	0.665***	13.8	0.599***	12.0
Market structure:				
* Average market share	0.015***	2.8	0.025***	4.4
* HHI (micro based)	− 0.013***	− 2.0	− 0.013***	− 2.2
* Entry-exit (firm demography)	0.326***	2.3	0.316***	2.2
Regulation indices:				
* Overall Cost of Doing Business	− 0.238***	− 5.5		
* Starting a business			0.01	0.6
* Closing a business			− 0.313***	− 3.0
* Employment inflexibility			− 0.144***	− 5.2
Industry dummies [b]	Yes		Yes	
No. of observations	1238		1238	
Log Likelihood	808.6		479.6	

[a] The smallest size class (1-9 employed persons) is taken as a benchmark. [b] The computer services industry (K720) is taken as a benchmark. [c] Codes, derived from z values: ** significant at 5% confidence level, *** significant at 1% level. Source: own calculations.

We use the estimates of the size class dummies to apply a sequence of Wald tests for testing the significance of differences between size class dummy estimates. The main results for the DEA scale efficiency models are presented in Table 8. The first entry concerns the estimate for the difference between size class 2 (10 – 19 employed persons) and the reference group (firms with less than 10 employed persons). In all models, this difference is very sizable and the result corroborates the descriptive results of Table 4. It suggests that there is much potential to gain in scale efficiencies for the smallest firms. However, the differences between the estimates of other size classes and size class 2 are very small and not significant different from zero, as can be inferred from the P-value of the χ^2 test statistics, which for all differences with respect to size class 2 exceeds its critical value of 0.05. Apart from the standard errors of the estimates the correlation between the errors of the estimates are also taken into account in the Wald test. The table also shows that size class 5 (≥ 250 employed persons) has a lower scale efficiency than size class 3 (20 – 49 employed persons) and size class 4 (50 – 249 employed persons). Thus the pattern of scale inefficiencies is bending back after size class 3. Taken on the whole these test results indicate that the most efficient scale is close to 20 employees and that scale inefficiencies show a hump shape pattern with strong potential scale economies for the smallest firms and diseconomies of scale for the largest firms

Table 8 Testing of differences between scale efficiencies of size classes

	SCE in Table 6, column 3		*SCE* in Table 7, column 1		*SCE* in Table 7, column 3	
	Estim.	P value	Estim.	P value	Estim.	P value
	a)	b)	a)	b)	a)	b)
Differences by pair of size classes:						
Size class 2 - Size class 1 [c)]	0.62	0.00 [c)]	0.72	0.00 [c)]	0.70	0.00 [c)]
Size class 3 - Size class 2	0.03	0.21	0.04	0.31	0.03	0.44
Size class 4 - Size class 2	0.03	0.25	0.04	0.28	0.02	0.60
Size class 5 - Size class 2	-0.06	0.05	-0.05	0.19	-0.10	0.02
Size class 4 - Size class 3	0.00	0.95	0.01	0.90	-0.01	0.83
Size class 5 - Size class 3	-0.09	0.00	-0.09	0.02	-0.12	0.00
Size class 5 - Size class 4	-0.09	0.00	-0.09	0.01	-0.12	0.00

a) Differences between estimates size class dummies RE Tobit models; b) P-value of $\chi2(1)$ test of equality of size dummy estimates. A P-value > 0.05 leads to accepting the null that size dummies are equal; c) P-value gives marginal significance of difference between estimate size class dummy 2 and estimate for reference group (size class 1). Source: own calculations.

.

6. Conclusions

We have investigated structural determinants of this labour productivity performance focussing on scale inefficiency, imperfect entry-exit selection, and regulatory barriers that hamper resource allocation to the most efficient firms. These issues have been investigated with a parametric global stochastic frontier (GSF) model, complemented with non-parametric data-envelopment analysis (DEA) as a robustness check and as a method for further exploring scale efficiencies. Having established industry-wise productivity frontier on the basis of a large dataset for 13 EU countries, we have for all observations calculated the distance to the productivity frontier and the incidence of scale inefficiencies. Subsequently we applied a Tobit panel estimator method to test whether market structure and national regulatory differences explain the resulting indicators for X-efficiency and scale efficiency.

The estimates reveal the following. The smallest size class (1-9 workers) represents more than 90 per cent of all business services firms in the EU and about one-third of total employment. This size class is very competitive, its firms on average have tiny market shares and firms within this size class tend to use similar technologies (small X-inefficiencies). However, this size class as a whole displays a huge scale inefficiency compared to the most efficient size class (50-249 workers). This scale inefficiency is persistent over time and points to weak competitive selection. Market and regulation characteristics explain the persistence of X-inefficiency (sub-optimal productivity relative to the industry frontier). More entry and exit are favourable for productivity performance, while higher market concentration works out negatively.

Regulatory differences also appear to explain part of the business services' productivity performance. In particular regulation-caused exit costs (closing down a firm) have a significant and large negative impact on the process of competitive selection and hence on productivity performance. To a lesser degree also regulation-caused inflexibility in labour reallocation lowers the productivity performance. We found no significant impact from policies with regard to starting up a new business. Overall we find that the most efficient scale in business services is close to 20 employees and that scale inefficiencies show a hump-shape pattern with strong potential scale economies for the smallest firms and diseconomies of scale for the largest firms. The smallest firms operate under competitive conditions, but they are too small to be efficient. And since this conclusion holds for about 95 out of every 100 European business services firms, this factor weighs heavily for the overall productivity performance of this industry.

Despite strong growth in terms of production and employment, the productivity growth track record of the European Union (EU) of business services industry has been bleak since many years. Policy makers have repeatedly expressed concerns about the stagnating growth of productivity in the business services industry (European Commission 2003), because of this industry's role as supplier of intermediary inputs and because of its key role in outsourcing. Our results suggest that future policies should give more weight to measures that facilitate firm growth to at least a size of 20 employed persons, and secondly to lower regulation-caused obstacles to reallocate labour and close inefficient firms. Both measures may have substantial positive effects for the productivity performance of EU business services.

ANNEXES

Annex 1 The representative firm by 'data cell'

A. Firm distribution between and within data cells.

Our data consist of constructed 'average firms' for each combination of 5 size classes, 8 sub-sectors and 13 countries in the cross-sectional dimension. We do not have specific information on the distribution of firms within each data cell (size class by sub-sector by country). Nonetheless our ‘average’ observations can be considered as representative firms for each data cell, using a discovery by Axtell (2001, 2006) from a statistical study on the size distribution of all U.S. business firms in 1997. On the basis of firm-level data he found that the distribution of firm-sizes over the total population closely follows the Pareto distribution with a shape parameter very near unity, which is often called the Zipf distribution. In the tail of the cumulative density function it holds that the probability that firm *i*'s employment size λ_i is smaller than some arbitrary size limit Λ is equal to:

$$\Pr[(\Lambda \geq \lambda_i] = \left[\frac{\lambda_o}{\lambda_i}\right]^{\alpha} \tag{A1}$$

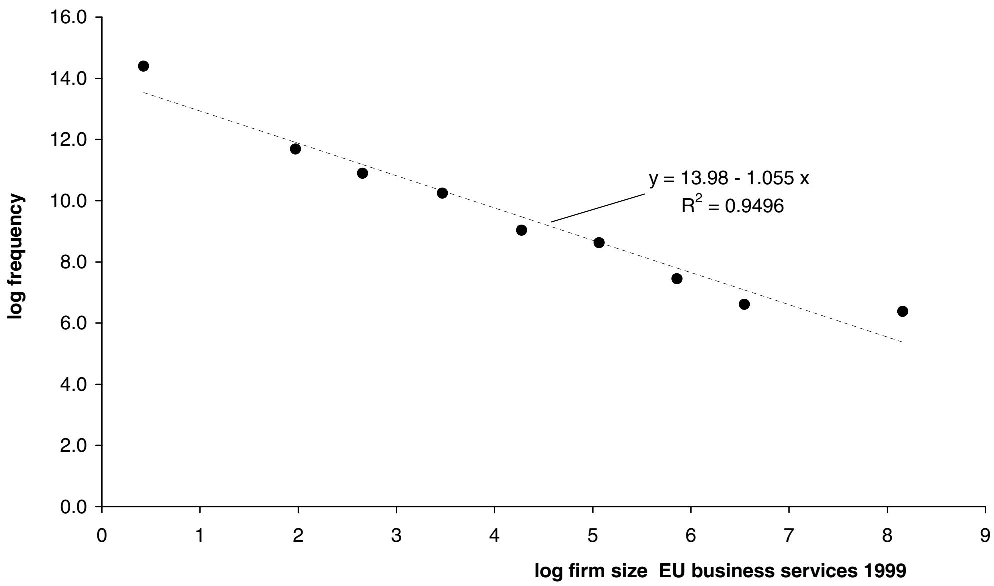
with λ_o being the minimum firm size and α the shape parameter of the distribution. For firms the minimum size is one employed person. Axtell found that for US business the shape parameter (α) had the value of *1.059*. This implies that the relation between the log of frequency and the log of firm size can be described as a straight downward-sloping line, i.e. the distribution is extremely skew. This result appeared to be robust when using other firm-size measures such as turnover (Axtell 2001, 2006). The Eurostat data on the EU business services include the total numbers of firms in each size class, thus allowing to implement the same test on firm-size distribution properties that Axtell did. The first test aggregates the data for all sub-sectors of business services and 11 EU countries in 1999. The result −shown in Figure A1− is remarkably similar to Axtell's outcomes. The estimated α in our case is even closer to unity: *1.055* which implies that the size distribution is "Zipfian".[11]

An important property of the Zipf-type Pareto distribution is that it is self-similar like a fractal, i.e. the distribution within size classes is similar to that prevailing over the entire size range. When we know the 'average' firm within a size class we indirectly know how this 'average' firm fits into the full intra-size class distribution of firms. The cumulative density function of each individual size class j with support $[MIN_j, MAX_j]$ then has a similar property:

$$\Pr\left[MIN_j \leq \lambda_{i,j} < MAX_j\right] = \int_{MIN_j}^{MAX_j} f(\lambda_{i,j})\, d\lambda_{i,j} = \left(\frac{MIN_j}{\lambda_{i,j}}\right)^{\alpha} \qquad \text{(A2)}$$

with $\lambda_{i,j}$ being the size of "average" firm i in size class j (cf. Johnson *et al.* 1994: 208; Axtell 2006). The implication of property (A2) is that once we have identified the "average" firm $\lambda_{i,j}$ we also have some information on the firms that within the size class distribution are located at the left and right of firm $\lambda_{i,j}$.

Figure A1 Size distribution of EU business services firms in 1999 (Eurostat data), log-log scale, size measured by number of employed persons



[11] The Gini coefficient with support [0,1] is calculated as $[2\alpha - 1]^{-1}$ and amounts to 0.9009, which confirms the very skewed character of the distribution.

With respect to scale effects, this property allows to derive in a stochastic sense some conclusions on a marginal change of firm size, so that standard scale analysis can be applied with regard to our dataset.

B. Representative firms and accuracy of the DEA method.

The fact that we do not have data available on to real firms or economic agents (in DEA terminology: Decision Making Units or DMU's) could introduce measurement error or parameter uncertainty. It is difficult to assess a priori what is the influence on the goodness of DEA estimates in general.

Recent advances in stochastic DEA approaches show that traditional DEA remains valid if the evaluator is risk neutral with respect to parameter uncertainty (e.g. Post 1999). Hence, the traditional DEA framework may serve as a benchmark for environments involving disturbances. A basic assumption for employing DEA is that the data form part of the production possibility set. We think it plausible to assume that this requirement is met by using average values for inputs and outputs, taking into account that the boundaries of the production possibility set are also determined by minimum and maximum values. The latter point clarifies why DEA results can be sensitive to the selection of DMU's. In real micro economic data, there is no guarantee of selecting the full production possibility set, especially not if the data are drawn from samples. But sample averages are by definition lying within the production possibility set! A further issue concerns the precise measurement of inputs and outputs. More formally, we can employ the following structure for the input-output estimates:

$$\begin{aligned} \hat{Y} &= Y + w_y \\ \hat{X} &= X + w_x \end{aligned} \qquad \text{(A3)}$$

with $\hat{Y}$ and $\hat{X}$ being estimates of true values for output (*Y*) and input (*X*). If these estimates are used rather than the true values, then selecting a reference unit (i.e. calculating the relevant comparison point on the frontier for each data point) becomes a problem of choice under uncertainty. In our data this uncertainty can be thought of as a set of overlapping circles drawn around the average values, with the ray of the circles representing the variance of the measurement errors *w*.

However, as holds for many problems of choice under uncertainty, this problem cannot be solved without making further assumptions regarding the distribution of the estimation errors. The most general forms of the theory of stochastic dominance (SD) show that traditional DEA remains applicable if the errors are random and mutually independent. Moreover, in our data we use sample averages so that the covariance matrices for *w* are given by the *1/N* multiples of the covariance matrices of the disturbances. Hence, the influence of measurement error seems not to play an important role in our data.

Annex 2 Correlation matrix for regulation indicators used

	Overall Cost of Doing Business	Starting a Business	Closing a Business	Employment Flexibility
Overall Cost of Doing Business	1.000			
Starting a Business	0.860	1.000		
Closing a Business	0.376	0.187	1.000	
Employment Flexibility	0.783	0.592	-0.010	1.000

References

Abramovitz, M., 1956, Resource and Output Trends in the United States Since 1870, *American Economic Review*, 46 (May), pp. 5-23.

Antonelli, C., 1999, The microdynamics of technological change, Routledge, London.

Axtell, R., 2006, Firm Sizes: Facts, Formulae, Fables and Fantasies, Center on Social and Economic Dynamics Working Paper No.44, Brookings, Washington.

Axtell, R., 2001, Zipf Distribution of U.S. Firm Sizes, *Science*, 293, pp.1818-1820.

Baker, P., and I. Miles, 2008, Study on industrial policy and services, Commissioned by the European Commission (DG Enterprise), ECORYS, Brussels / Rotterdam.

Barone, G. and F. Zingano, 2008, Service regulation and growth: evidence from OECD countries, Temi di Discussione #675, Banca d'Italia, Rome.

Bartelsman, E. and M. Doms, 2000, Understanding productivity: lessons from longitudinal microdata, *Journal of Economic Literature*, 83 (3), 569-594.

Battese, G. and T. Coelli, 1995, A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data, *Empirical Economics*, 20 (2), 325-32.

Bloch, H., G. Madden and S. Savage, 2001, Economies of scale and scope in Australian telecommunications, *Review of Industrial Organization*, 18 (2), pp. 219-227.

Brown, C, J. Haltiwanger and J. Lane, 2006, Economic turbulence: is a volatile economy good for America?, University of Chicago Press, Chicago.

Camacho, J. and M. Rodriguez, 2007, Integration and diffusion of knowledge-intensive services for industry performance, in: L. Rubalcaba and H. Kox (eds.), Business services in European economic growth, Palgrave MacMillan, Basingstoke, 128-143.

Cantner, U., 2007, Firms' differential innovative success and market dynamics, Jena Economic Research Papers 2007-078, Jena.

Caves, R., J. Khalilzadeh-Shirazi and M.E. Porter, 1975, Scale economies in statistical analyses of market power, *The Review of Economics and Statistics*, vol. 57 (2), pp. 133-40.

Coelli, J., D. Prasada Rao, C. O'Donnell and G. Battese, 2005, An Introduction to Efficiency and Productivity Analysis, Springer, New York.

Copenhagen Economics, 2005, Economic Assessment of the Barriers to the Internal Market in Services, commissioned by the European Commission, Copenhagen/ Brussels.

CSES, 2001, Barriers to trade in business services - Final report, Report commissioned by the European Commission, Centre for Strategy & Evaluation Services / European Commission, Brussels.

De Wit, G., 2005, Firm size distributions - an overview of steady-state distributions resulting from firm dynamic models, *International Journal of Industrial Organization*, 23, 423-450.

Diewert, E., 2005, Progress in service sector productivity management, *International Productivity Monitor*, 11, 57-69.

Dixit, A. and J. Stiglitz, 1977, Monopolistic competition and optimum product diversity, *American Economic Review*, 67, 297-308.

Djankov, S., R. La Porta, F. Lopez, and A. Shleifer, 2002, The regulation of entry, *Quarterly Journal of Economics*, 117 (1), pp 1-37.

Djankov, S., E. Glaeser, R. La Porta, F. Lopez-de-Silanes and A. Schleifer, 2008, The new comparative economics, World Bank / Harvard University, mimeo (unpublished).

European Commission, 2003, The competitiveness of business-related services and their contribution to the performance of European enterprises, COM(2003) 747 final, Brussels.

Foster, L., J. Haltiwanger and C. Krizan, 1998, Aggregate productivity growth: lessons from microeconomic evidence, NBER Working Paper 6803, NBER, Cambridge MA.

Frisch, R., 1965, Theory of production, D. Reidel, Dordrecht.

Grönroos, C. and K. Ojasalo, 2004, Service Productivity: towards a conceptualization of the transformation of inputs into economic results in services, *Journal of Business Research*, 57, 414 – 423.

Guerrieri, P., and B. Maggi, 2005, Technology diffusion, services and endogenous growth in Europe: is the Lisbon strategy useful?, IMF Working Paper WP/05/103, IMF, Washington.

Gust, C. and J. Marquez, 2002, International comparisons of productivity growth: the role of information technology and regulatory practices, International Finance Discussion Papers, Number 727, Board of Governors of the Federal Reserve System.
Hempell, T., G. Van Leeuwen and H. van der Wiel, 2002, ICT, innovation and business performance in services: evidence for Germany and The Netherlands, OECD-DSTI, Paris.
Johnson, N., S. Kotz and N. Balakrishnan, 1994, Continuous univariate distributions, John Wiley & Sons, New York.
Jovanovic, B., 1982, Selection and the evolution of industry, *Econometrica*, 50, 649-670.
Kumbhakar, S., S. Gosh, S. and J. McGuckin, 1991, A generalized production frontier approach for estimating determinants of inefficiency in US dairy firms, *Journal of Business and Economic Statistics*, 9, 279-286.
Klapper, L., L. Laeven and R. Rajan, 2006, Entry regulation as a barrier to entrepreneurship, *Journal of Financial Economics*, 82 (3), 591-629.
Kocsis, V., R. Lukach, B. Minne, V. Shestalova, N. Zubanov and H. van der Wiel, 2009, Relation between entry, exit and productivity, CPB Document No. 180, CPB Netherlands Bureau for Economic Policy Analysis, The Hague.
Kox, H., 2004, The contribution of business services to aggregate productivity growth, in: G. Gelauff *et al.* (eds), Fostering productivity: patterns, determinant and policy implications, Contributions to Economic Analysis #263, Elsevier Science, Amsterdam, 243-264.
Kox, H. and A. Lejour, 2006, The effect of the Services Directive on intra-EU trade and FDI, *Revue Economique*, 57 (4), 747-769.
Kox, H., A. Lejour and R. Montizaan, 2004, The free movement of services within the EU, CPB Document 69, CPB Netherlands Bureau for Economic Policy Analysis, The Hague.
Kox, H., G. van Leeuwen and H. van der Wiel, 2007, Market Structure, Productivity and Scale in European Business Services. Chapter 11 in “Business services in European economic growth”, Palgrave MacMillan, Basingstoke/ New York.
Leeuwen, G. van, 2008, Innovation and performance, a collection of microdata studies, PhD dissertation, Delft University of Technology, Delft.
Leibenstein, H. (1966), Allocative Efficiency vs. X-Efficiency, *American Economic Review*, 56 (3), 392-415
Muller, E. and A. Zenker, 2001, Business services as actors of knowledge transformation: the role of KIBS in regional and national innovation systems, *Research Policy*, 30 (9), 1501-1516.
Nicoletti, G. and S. Scarpetta, 2003, Regulation, Productivity and growth: OECD evidence, OECD Economic Department Working paper 347, Paris.
H. Nordås and H. Kox, 2009, Quantifying regulatory barriers to services trade, OECD Trade Policy Working Paper No. 85, OECD, Paris.
Olley, G. and A. Pakes, 1996, The dynamics of productivity in the telecommunications equipment industry, *Econometrica*, 64, pp. 1263-1297.
Oulton, N., 2001, Must the growth rate decline? Baumol's unbalance growth revisited, *Oxford Economic Review*, 53, 606-627.
Paterson, I., M. Fink, and A. Ogus, 2003, Economic impact of regulation in the field of liberal professions in different Member States - regulation of professional services, Institute for Advanced Studies, Vienna.
Pels, E., P. Nijkamp and P. Rietveld, 2003, Inefficiencies and scale economies of European airport operations, *Transportation Research Part E: Logistics and Transportation Review*, 39(5), 341-361.
Post, T., 1999, Finding the Frontier, Methodological Advances in Data Envelopment Analysis, Ph.D Thesis, Erasmus University, Rotterdam.
Rajan, G. and L. Zingales, 1998, Financial Dependence and Growth, *American Economic Review*, 88 (3), 559-86.
Rubalcaba, L. and H. Kox, 2007, Business services in European economic growth, Palgrave MacMillan, Basingstoke/ New York.
Schreyer, P., 2001, Measuring productivity - measurement of aggregate and industry-level productivity growth: OECD manual, OECD, Paris.
Schure, P. and R. Wagenvoort, 1999, Economies of scale and efficiency in European banking: new evidence, Economic and Financial Report 1999/01, European Investment Bank, Luxembourg
Shy, O., 2001, The economies of network industries, Cambridge University Press, Cambridge.
Silk, A. and E. Berndt, 2003, Scale and Scope Economies in the Global Advertising and Marketing Services Business, HBS Research Paper No. 03-10.
Triplett, J. and B. Bosworth, 2004, Productivity in the US services sector: new sources of economic growth, Brookings Institution Press, Washington.

Vernon, R., 1966, International investment and international trade in the product cycle, *Quarterly Journal of Economics*, 80, 190-207.

Viitamo, E., 2007, Productivity of business services - towards a new taxonomy, Research Report #188, University of Technology, Lappeenranta (Finland).

Zellner, A., J. Kmenta, and J. Drèze, 1966, Specification and Estimation of Cobb-Douglas Production Function Models, *Econometrica*, 34 (4), 784 – 795.