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Determinantes estructurales de la productividad de los servicios a empresas en EU

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Structural determinants of productivity in European business services

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Abstract:

The paper investigates the structural factors that affect labour productivity performance in European business services. We estimate the productivity frontier for eight business services sectors and five size classes. Subsequently, we explain the distance of firms to the productivity frontier (X-inefficiencies) and scale efficiency by market structure characteristics, entry- and exit intensity, and national regulatory features. The frontier is assessed both by parametric and by nonparametric methods on a data panel for 13 EU countries. We find that scale effects are important in business services; firms with less than 20 employees experience substantial scale-related productivity disadvantages. Productivity performance of firms is improved by having more competitors and more dynamic entry-exit selection, while market concentration and regulation intensity work out negatively.

Key words: business services; European Union; labour productivity; frontier models (GSF, DEA); market structure; entry-exit; scale efficiency; regulation

JEL codes: **L11, L8, L5, J24, D2, K23**

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1. Introduction

This paper aims to assess the structural determinants of labour productivity performance in the business services industry of the European Union, thereby focussing on the role of scale effects, market structure, entry-exit selection, and regulation.

Business services has become one of the biggest EU industries in terms of employment. It is a major supplier of intermediary inputs to other industries, including IT services, and many other knowledge-intensive inputs.[1] This industry has a key role in recent outsourcing trends. Despite the strong growth of business services in terms of production and employment, its productivity growth record is meagre. Based on OECD national accounts data, the annual productivity growth of business services between 1979 and 2003 amounted to −0.3 per cent in the EU15 countries. Rubalcaba *et al.* (2007) show that the productivity growth stagnation hardly differs between knowledge-intensive and other the business services.[2]

Policy makers have repeatedly expressed concerns about the stagnating growth of productivity in the business services industry (European Commission 2003). Increasing outsourcing of activities to an industry with stagnating productivity might reduce the competitiveness of client industries, and eventually lower the aggregate rate of growth in the EU. Barone *et al.* (2008) indeed find 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 2009; Hempell *et al.* 2002; Antonelli 1999). Therefore, Kox (2004) and Baker *et al.* (2008) 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.[3] Baker *et al*. (2008) in their two volume study however call for "*a better understanding of the factors that drive productivity performance within services sectors*". It is in this problem area that we position the present paper on structural determinants of labour productivity in European business services.

We hope to make a positive contribution to the literature by identifying and quantifying some key factors that determine the productivity performance of business services industry. Our empirical results are based on a two-step research approach. We first estimate the productivity frontier per sub-sector and size classes, using a data panel for thirteen EU countries. The productivity frontier is subsequently assessed by parametric and nonparametric methods. In a next step we explain the distance of business-services firms to the productivity frontier. We include the following structural determinants: scale efficiency, market structure, entry- and exit dynamics and national regulatory features.

What we find is that scale effects are important and that firms with less than twenty employees experience substantial scale-related productivity disadvantages. The persistence of X-inefficiency (sub-optimal productivity relative to the industry frontier) can be explained by market and regulation characteristics. More dynamic entry and exit are favourable for productivity performance, while market concentration works out negatively. Also regulation intensity appears to lower productivity performance in EU business services. In particular we find that regulation-caused exit costs (closing down a firm) have a very significant negative impact on the process of competitive selection and hence on productivity performance of EU business services.

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 empirical models that we will be testing, 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. Since scale economies form an important part of our analysis, we need sufficient data on small firms, which data turned out not to be readily available across countries. Section 4 describes how we have solved this data problem and we present some descriptive results on the basis of these data and other main variables. Section 5 presents the econometric results. The concluding section 6 summarises the main findings on the structural productivity determinants in business services and some possible implications for economic policy.

2. Productivity determinants in business services: literature review

The literature offers a number of candidate explanations for stagnating productivity growth. 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. For a number of these explanations (workforce and management quality, measurement error) it is difficult to imagine how they could explain differences between services sectors and between countries (EU-USA). We want to focus on three groups of explanatory factors: (a) technology and scale inefficiency; (b) market structure and dynamic entry-exit selection; and (c) regulatory barriers.

2.1 Technology and 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. If the range of relevant technologies differs between size classes, there may be variable or ‘local’ ‘scale economies within one industry. 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.

If services firms have fixed set-up costs their average costs are a negative function of production scale. The market standard for a services sector may be such that the efficient production and distribution of services requires some minimum-efficient scale.

Operating below this threshold either makes marginal costs too high given market prices, or otherwise the delivered service is too inefficient for being acceptable to clients. Along either of these channels, scale diseconomies will have a negativity effect on the productivity of these services firms.

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.[4] 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).[5] 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 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" (Leibenstein 1956, 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. The integration of European markets for services still has a long way to go (CSES 2001; Copenhagen Economics 2005; Kox *et al.* 2004, 2006).[6]

If firms over time persistently have a productivity underperformance in European business services, this either indicates that imperfect competition prevails, or that the industry has not yet arrived in a steady-state. Regarding the latter point, the concept of industry life cycles (Vernon 1966) deserves another look, as some branches of the business services industry did not even exist 20 years ago. Vernon 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.

Service markets have a long history of regulation, caused by market failures that may play a role in the production, distribution and consumption of services.[7] 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 as the Text Box 1 below demonstrates.

<insert Text Box 1 about here>

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 firm 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.[8] 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.

Summing up, from this brief review of the literature we conclude that the weak productivity growth performance of European business services can have multiple, interrelated causes. Likely explanatory factors are: (a) scale inefficiency, (b) imperfect competition in relation with malfunctioning entry-exit selection, and (c) regulatory barriers that hamper resource allocation to the most efficient firms.

3. Empirical strategy

Our modelling strategy aims at investigating the following three elements of competitive selection in EU business services:

- The presence of variable returns to the production scale;
- After identifying a productivity frontier for all data (and controlling for frontier productivity differences between sub-sectors, countries, size classes and time) we test whether there exist any systematic difference in X-inefficiencies between size classes in the incidence of sub-frontier productivities;
- The presence of scale related inefficiencies as an additional cause of sub-frontier productivity and the role of market and regulatory characteristics in explaining differences in scale inefficiencies.

The analysis of scale economies and efficiency frontiers can be done by a Generalized Stochastic Frontier (GSF) model (e.g. Khumbakar *et al.* 1991; Kox *et al*. 2007). 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. Moreover using DEA inefficiencies allows us to look deeper into the nature of the scale effects.

3.1 GSF-model.

The availability of panel data enables us to apply the GSF-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. We start from a value-added production function (1) as 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 specification to get labour productivity as the dependent variable, the two-equation GSF-model reads:

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

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

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 $\mathbf{B}$ 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 $\mathbf{Z}$ and that deviations from these means are random ('white noise'), represented by θ. This random variable 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, i.e. $\theta_{it} \geq -\gamma'\mathbf{Z}_{it}$.[9]

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. Summing up, 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 $\mathbf{B}$ 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 $\mathbf{Z}$ vector.
- Size-related X-inefficiencies (included also in Z) are estimated after controlling for exogenous market structure variables and regulation variables.

3.2 DEA model.

Parametric models like the GSF-extension of the translog model may cope with the stochastic nature of the relation between output and inputs. However, although rather flexible, the GSF model imposes a restrictive functional form as well as 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.[10]

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. However, it imposes some rigid assumptions such as the supposition that all size classes can apply the same technology and that scale effects occur over the entire scale range . For instance, translog estimates can suggest the presence of constant returns to scale (CRS), whereas we have in reality variable returns to scale (VRS). The fitted GSF technology is an "average" or sample-wide estimate, which may not represent scale behaviour at lower levels. Therefore, even if the CRS is not rejected "on average" by the translog estimates, still many firms can 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.

We address these issues by applying a robustness check with Data Envelopment Analysis (DEA). The DEA-model offers an interesting alternative for the GSF-model for investigating scale effects and their interaction with market structure. This method does not impose an a priori structure on productivity relations of interest. Whereas efficiency estimates in GSF are directly related to the model parameters (assumed unbiased), this is not the case for DEA.

The DEA method applies 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 implementation choices have to be made. We presume 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 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. Using H as symbol for (average) productivity the VRTS X-efficiency indicator reads:

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

DEA also allows to calculate 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 firm-size is larger or smaller than the optimal scale, X-efficiencies will be smaller (closer to 0) for CRTS than for VRTS. 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:

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

with $\mathbf{X}$ representing a vector of dummy variables for industries and size classes and $\mathbf{Z}$ 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 results

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 have decided to solve the data availability problem by using Eurostat's New Cronos Structural Business Statistics (SB) 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 can thus *construct* a representative firm or decision-making unit (DMU, as it is called in data envelopment analysis) 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 required 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 had to homogenise classifications at the lowest common denominator, thus sacrificing some available sub-sector and size-class detail and years in the data from some countries.[11] Homogenisation across countries yielded a fully comparable set of data on business services industry in 13 EU countries, eight sub-sectors and five size classes for the period 2000-2005.

As central productivity index for this study we have chosen for a straightforward labour productivity measure, defined as value added per employed full-time person. The data would have allowed to construct 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.

Figure 1 shows that the size-class dimension of the data set shows some interesting 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 fallen 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.

<.. add Figure 1 about here...>

Table 1 presents some descriptive statistics on the country variation in the data set. With on average 182 data cells per country we have a total of 2362 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 in most 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.

< insert Table 1 about here >

Table 1 also shows country differences with respect to four regulatory variables that will be used for explaining of the inter-country differences in productivity and scale efficiency. The first variable is the so-called PMR indicator of the OECD that measures relative differences in the overall intensity of product-market regulation (cf. Nicoletti *et al*. 2002, 2003). This variable shows relatively limited variation between countries. The other three regulation indicators have been derived from the World Bank Cost of Doing Business database. The measurement procedure differs from the OECD approach. It quantifies national differences in regulation-caused cost of doing business by quantifying how precisely defined identical business plans would be handled by national regulatory systems (cf. Djankov *et al*. 2008 and www.doingbusiness.org). This captures both the relative strictness of the regulations themselves and the efficiency of the regulatory apparatus. For this paper we have used the World Bank data to calculate three indicators: one general indicator covering eight business areas, and two indicators for business areas that seem particularly important for our research, namely an indicator for the costs of setting up a new firm and one for the flexibility in employment contracts. The precise calculation method is documented in Kox *et al*. (2009). The different indicators show considerable variation between countries.

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 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.

< insert table 2 about here > .

The table also shows average differences with regard to three indicators for market structure. The three indicators for market structure have been constructed by merging the Eurostat SBS panel with the Eurostat data on firm demography that contains data on the number of new-born, exiting and active incumbent firms for a subset of branches and countries. We used the union of the two data sets to construct the 'net' entry-exit rate, scaled by the number of active incumbent firms by country, industry and year. Subsectors 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 (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.

< insert Figure 2 (capital intensity by size) about here >

The computer services industry displays an U-shaped capital intensity picture, 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 main frame systems per employee.

5. Econometric results

The results will be presented according to the three-step testing strategy (cf. beginning of section 3). Section 5.1 brings the estimation results for the GSF model, with the logarithm of the productivity level as dependent variable. Section 5.2 compares the parametric X-efficiency predictions of the GSF model with the corresponding results for the non-parametric DEA model.[12] Section 5.3 explains the X-efficiencies and scale-efficiencies with market-structure and regulation variables. In section 5.4 we check for the robustness of these findings by adding entry-exit dynamics. The final section tests for the differences between scale inefficiencies across size classes and shows that a minimum-efficient size of operation can be identified.

5.1 Results GSF-model

Table 3 presents the test results for the GSF model using the method of Battese and Coelli (1995). Along with the technology variables of the production function, we apply indicators for market characteristics and national regulation as control variables. We use the Hirschmann-Herfindahl index (HHI) for market concentration. As an indicator for competition intensity we further apply the average market share per data cell (country x industry x firm size), normalised for country size.[13] The variables for national regulation intensity are lagged one year which we assume to be a reasonable reaction time for firms.

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

< insert Table 3 about here >

Panel B of Table 3 presents the simultaneous estimates for equation (2) of the GSF model. Here we introduce average market share per data cell and the HHI index as indicators for market structure. For the impact of regulation intensity we use the World Bank-derived ‘Cost of Doing Business’ indicator.

For the interpretation of the estimation 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. We thus find here 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.[14]

A remarkable result is that a higher regulation intensity (‘Cost of Doing Business’ index) has a very significant negative effect on X-efficiency. This is in line with the predictions from the literature (cf. section 2). Finally, market concentration as measured by the HHI appears not to have a significant impact on X-efficiency in the GSF estimates.

5.2 Comparison with DEA

We use data-envelopment analysis (DEA) both a robustness check on the GSF results and as a method that allows us 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 XE^{VRTS} results appear to be rather similar to the GSF-predictions for the smallest and the largest size classes. However, for the other size classes we find pronounced differences. This is not surprising, because a non-parametric variable-returns-to-scale frontier always envelops the data more tightly when than the constant-returns-to-scale technology. Averaged over all observations, the

Comment [GvL1]: Verwijderd omdat we bij GSF geen CRS hebben opgelegd

GSF model overestimates the X-efficiency in comparison to the preferred XE^{VRTS} measure, while the XE^{CRTS} indicator tends to underestimate it.

< insert Table 4 about here >

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. We have pictured the three most relevant efficiency indicator into one graph (Figure 3). The results are quite spectacular. The smallest size class has the least degree of X-inefficiency according to XE^{VRTS} (and about the GSF average). It means that *within* this size class firms apply very 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.

<........insert Figure 3 about here ....>

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).[15] 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 that we find, 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.

< .... insert Table 5 about here ......>

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. A logical next step in our test is therefore to investigate whether scale efficiencies in the panel dimension can be explained by market-structure and regulation. We try to explain the DEA efficiency scores in a series of Tobit regression models. Since we cannot identify whether individual firms move between size classes, we use a random-effects panel estimator instead of relying on a fixed-effects model.[16]

For regulation we now use a more detailed set of indicators. In Table 3 regulation we used the 'Cost of Doing Business' indicator that is broad-coverage 'umbrella' indicator. Regarding possible policy consequences we can however learn more by looking at more specific indicators, to understand better which regulation areas matter most for productivity and scale economies. Hence, we replace the composite regulation variable by the following three sub-indicators, each covering a specific area of regulation:

1) The costs of starting up and registering a new business (entry costs);
2) The regulation-caused costs of closing a business (exit costs), and
3) The indicator for inflexibility in employment contracts (representing national differences in costs for labour reallocation, hiring and firing).

A higher score on either of these indicators implies more regulation-caused costs for firms. Table 6 presents the marginal effects 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 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 intra-segment competition intensity does not appear to be statistically significant, however. The estimates for the regulation indicators show that regulation-caused entry costs, exit costs and employment inflexibility all have a negative impact, with by far the largest effect coming from exit costs.

< Insert Table 6 about here >

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-sizeclass 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 market concentration works out negatively on productive efficiency.

Another very interesting result from Table 6 relates to the results for the different regulation variables. All have the expected negative sign, but the estimated parameter for the impact of regulation-caused start-up costs on scale efficiency is now close to zero. Most entry occurs in the smallest size class which as table 1 showed is already very crowded. So, we may conclude that regulation-caused entry costs play no role for the large scale inefficiency of the smallest size class (Figure 3). By far the largest regulatory obstacle for competitive selection and efficiency appears to be the role of exit costs, the regulation-caused costs of closing a firm, followed only at distance by the role of regulation-caused employment inflexibility.

5.4 Adding information on the dynamics of entry and exit

The regulation variables in Table 6 might pick up the role 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.

< Insert Table 7 about here >

As expected, the contribution of entry-exit is positive as this measure provides an additional competition element above the impact of competition between incumbent firms. More net entry increases the incentive to gain in efficiency and this impact on efficiency turns out to be rather considerable.

More striking however, 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 role 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 record of business services in the EU.

5.5 Testing for optimal scale size

Another feature of our data is that we can test for the existence of an optimal scale of operation in business services. This can be achieved by using the estimates of the size class dummies. These estimates can be interpreted as the difference in scale efficiencies between size classes, conditional on including 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).

< Insert Table 8 about here >

We used the estimates of the size class dummies to apply a sequence of Wald test for the differences between size class dummy estimates. The results for the four 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 this result corroborates the descriptive results of Table 4. Arguably, there seems to be 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.[17]

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.

6. Conclusions

The present analysis is triggered by the weak productivity performance of the business services industry in the European Union. We have investigated the structural determinants of this labour productivity performance, thereby focussing on scale inefficiency, imperfect competition in relation with malfunctioning entry-exit selection, and regulatory barriers that hamper resource allocation to the most efficient firms. These issues have been investigated with a parametric GSF productivity frontier 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 established the distance to the productivity frontier and the incidence of scale inefficiencies. Subsequently, we applied a Tobit panel estimator method to test whether the resulting indicators for X-efficiency and scale efficiency could be explained by market structure characteristics and national differences in regulation intensity.

We have a number of important results. 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 very similar technologies (leading to 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. The persistence of X-inefficiency (sub-optimal productivity relative to the industry frontier) can be explained by market and regulation characteristics. More dynamic entry and exit are favourable for productivity performance, while market concentration works out negatively. Also regulation intensity appears to lower productivity performance. Zooming in further on the type of regulation, we find that in particular regulation-caused exit costs (for closing down a firm) have a very significant negative impact on the process of competitive selection and hence on productivity performance of EU business services. To a lesser degree also regulation-caused inflexibility in labour reallocation lowers the productivity performance. Remarkably enough, policies with regard to setting up a new business have no significant impacts. Hence, regulation-caused exit cost for firms appear to be a major obstacle to an effective competitive selection. Overall we find 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.

The results indicate that policies in the first place 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.

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ANNEX 1 The representative firm by data cell

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:

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

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".[18]

< insert Figure A1 about here >

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-sizeclass distribution of firms. The cumulative density function of each individual size class *j* with support [MIN_j , MAX_j] then has a similar property:

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

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 the firm $\lambda_{i,j}$. 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.

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:

$$\begin{aligned}\hat{Y} &= Y + w_y \\ \hat{X} &= X + w_x\end{aligned}$$

, 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.

Text boxes, Figures and Tables

** **beginning of Text box 1** ****************

National regulation in knowledge-intensive business services

Fixing qualifications to practice (input-related)
- certification requirements for necessary education and experience
- requirements on membership of national branch organisations
- definitions of professional titles and protection of their use
- post-qualification educational requirements
- regulation on employments contracts, hiring and firing

Fixing standards of professional competence (output-related)
- ethical standards, codes of conduct
- technical performance standards
- requirements for professional indemnity and liability insurance
- requirements pertaining to organisational structure of the firm

Regulations affecting competitive conditions
- prohibitions against business relations with other professionals
- restrictions on entry (by law, by delegated authority of branch organisations)
- restrictions on price-setting
- restrictions on advertising and marketing

** **end of text box 1*****************

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:		Intensity product market regulat. [c)]	Overall cost of doing business [d)] 2005	Cost of starting up a new firm [e)]	Flexibility in employ-ment contracts index [f)]
					total no. of firms	total employ-ment	2003		2005	2005
Austria	196	42	243	28.4	91.3	35.6	1.40	0.76	0.61	0.69
Belgium	184	76	386	33.8	95.7	28.5	1.40	0.69	0.61	0.62
Danmark	96	16	108	37.6	91.4	24.6	1.10	0.55	0.19	0.20
Finland	98	16	81	33.2	94.1	33.6	1.30	0.67	0.25	1.09
France	240	399	2684	29.7	93.5	24.2	1.70	0.79	0.26	1.40
Germany	240	344	3242	28.6	87.0	23.0	1.40	0.84	0.60	1.34
Ireland	103	11	70	34.4	91.5	36.4	1.10	0.65	0.38	0.50
Italy	240	739	2059	28.0	97.5	53.0	1.90	1.08	0.66	0.83
Netherland	230	104	677	42.1	91.7	24.8	1.40	0.80	0.53	1.02
Portugal	193	60	281	12.6	96.2	37.0	1.60	1.12	1.06	1.56
Spain	160	378	1918	18.9	95.2	34.7	1.60	1.12	1.01	1.54
Sweden	207	141	453	30.4	96.7	43.2	1.20	0.80	0.25	0.96
Un.Kingdo	175	426	3234	44.0	91.2	26.8	0.90	0.44	0.34	0.29
Total	2362	2751	15436							
Average	182	212	1187	30.9	93.3	30.9	1.38	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) OECD umbrella indicator of the relative intensity of product-market regulation; ranks from 0 (lowest) to 6 (highest regulation intensity), covering a large number of economic regulation areas. For calculation see Nicoletti et al. (2000). d) 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. Kox et al. 2009). e) 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). f) 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. Kox 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. OECD PMR regulation indicators derived from OECD Economics Department. Other regulation indicators derived from World Bank Cost of Doing Business database (for calculation method, see: OECD 2009).

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 New Cronos data, SBS and EUKLEMS data.

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

	Dependent variable: Log(labour productivity)	
	Estimate [c)]	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 [a)]	− 0.04***	− 4.0
* HHI, Herfindahl index, micro-based	− 0.23	− 0.5
Regulatory environment:		
* Overall Cost of Doing Business indicator [b)]	1.41***	6.6
Size dummies included	yes	
No. of observations	2362	
Log Likelihood	366.6	

a) Reciproque of the number of firms per data cell (country x industry x size class).
b) Composite indicator of regulation-caused cost of doing business (0 is lowest level) in a country relative to a 60-country sample, based on 28 sub-indicators in World Bank Cost of Doing Business database. The construction of the indicator is described in Kox *et al.* (2009).
c) Codes: * significant at 10% confidence level, ** significant at 5% level, *** significant at 1% level.

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

	Predicted efficiency GSF-model [a)] (median for size class)	Calculated X-efficiencies on basis of DEA-model [b)]	
		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).

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).

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 (WB):				
* 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.

Table 7 DEA scale efficiencies estimated by Random Effects Tobit model after including net entry-exit rates (based on merged SBS and Firm Demography data), 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 (WB):				
* Overall Cost of Doing Business	− 0.238***	− 5.5		
* Starting a business			0.01	0.6
* Closing a business			− 0.313***	− 3.0
* Employment flexibility			− 0.144***	− 5.2
Industry dummies [b]	yes		yes	
No. of observations	1238		1238	
Log Likelihood	126,2		138,1	

[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.

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. a)	P value b)	Estim. a)	P value b)	Estim. a)	P value 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
0Size 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 $\chi 2(1)$ 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.

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

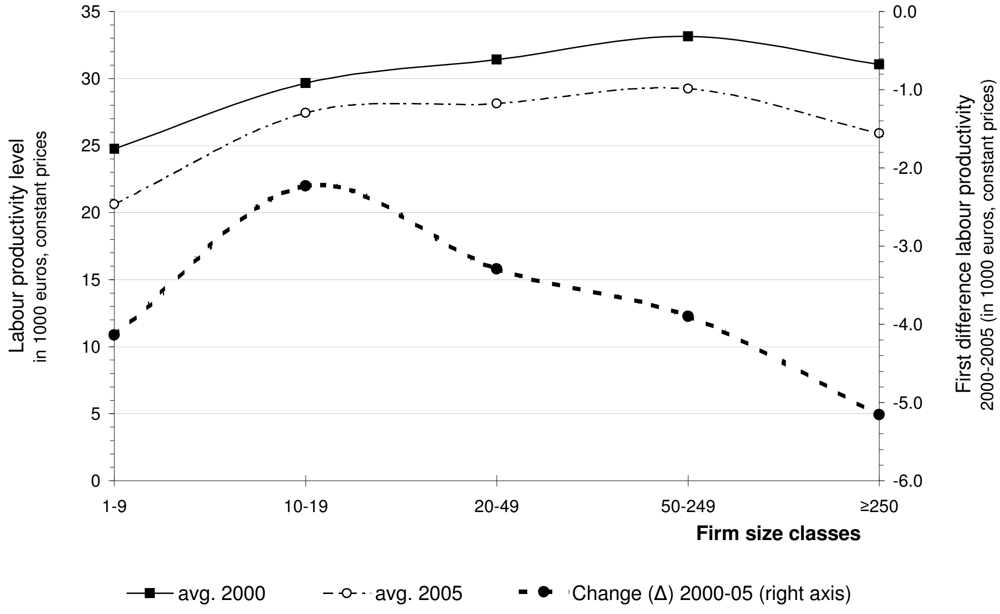


Figure 2 Capital intensity per employed worker, 2000-2005 average by industry

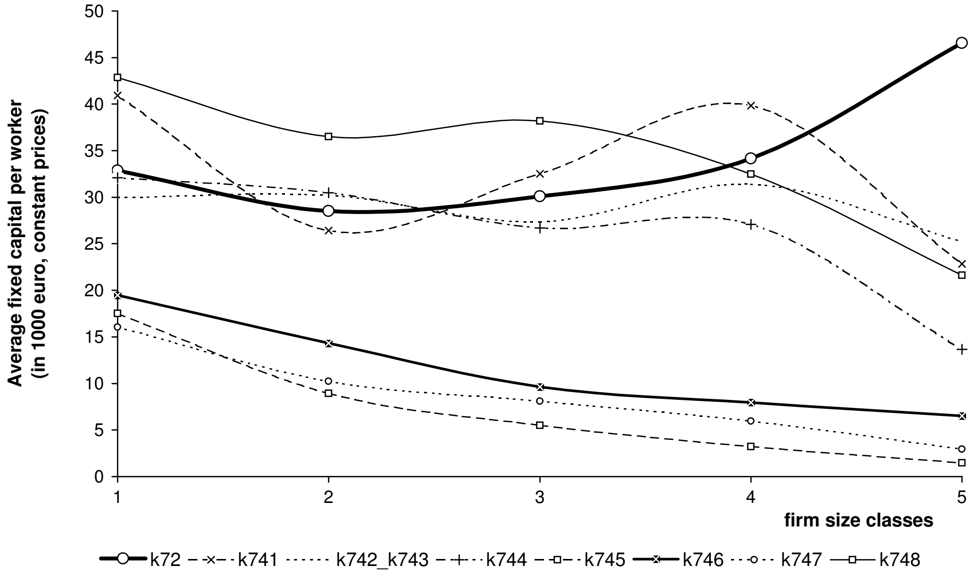
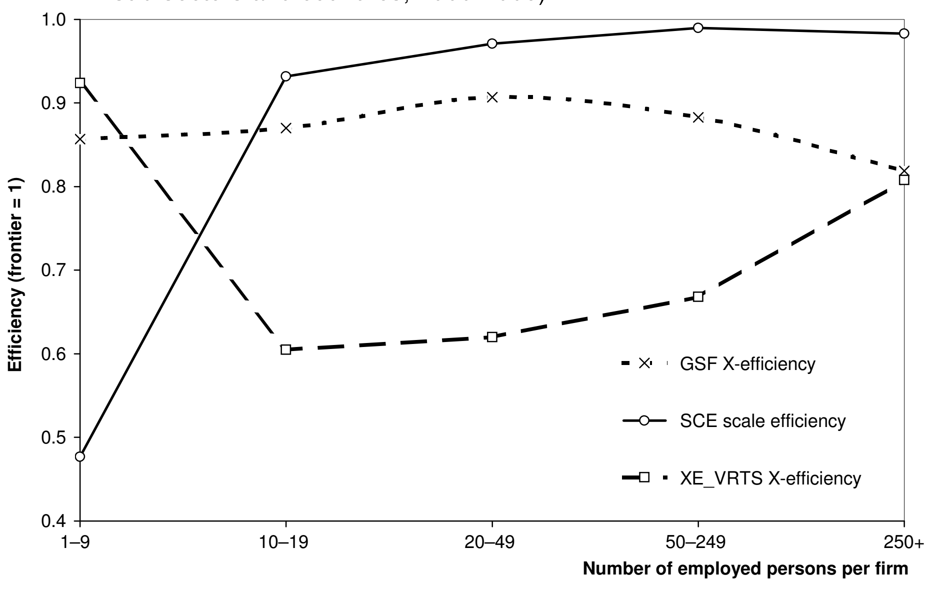
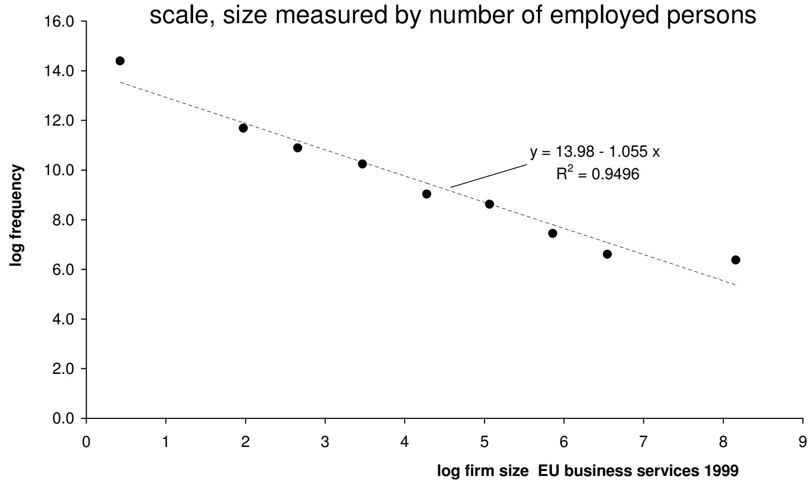


Figure 3 A comparison of three efficiency indicators by size class (average all sub-sectors and countries, 2000-2005)



to be added in annex 1:

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



Endnotes

[1] Eurostat data for 2004 show that 3 million enterprises in the EU-27 had the provision of business services as their main activity. They employed 13 million persons and generated total gross turnover of 1167 billion euros, equivalent to 11% of employment in the commercial economy. Legal, accounting, auditing and business management services accounted for 35% of business services turnover, information technology (IT) consulting for 27%, architecture, technical engineering and consultancy held 19 %, advertising 11%, and labour recruitment and provision of personnel another 8%.

[2] Note that the average productivity level in many branches of business services is quite high compared to the 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.

[3] Camacho and Rodriguez (2007) and Guerrieri (2005) offer empirical evidence for the generation of technological spillovers by business services.

[4] Compared to manufacturing, scale economies in services are much less investigated, partly related to data availability problems (cf. Triplett *et al.*, 2004; Diewert 2005).

[5] Several authors found empirical evidence for dynamic productivity-related selection effects (Foster et al. 1998; Brown et al. 2006; Van der Wiel 1999).

[6] The business services branches IT consultancy, equipment renting and personnel recruitment are most exposed to foreign competition. The branches most sheltered from foreign competition are accountancy and tax consultancy (CSES 2001).

[7] The most important market failures that are addressed by regulation are externalities and information asymmetry. Externalities may occur as the production, distribution or consumption of some services causes economic impacts for third parties (reliability of audited annual company reports for the functioning of the overall financial system, or the public safety aspects of building design). Moreover, the production and consumption of the service products often cannot be separated in place and time, making it difficult to standardise a service product. The quality of the product is a priori uncertain for the consumer – more than holds for commodities. In the case of a simple service product such as a haircut, this uncertainty problem is generally manageable. The information problem for the individual service buyer is however more serious in the case of more complex professional and medical services that require the input of specialist knowledge. The buyer of such service products is confronted with a structural information asymmetry as to the quality of the service product, sometimes even after the transaction took place. To repair such structural asymmetries government authorities are inclined to regulate professional and business services where information asymmetry may be relevant, even if the services are mainly supplied to companies.

[8] For instance, Baker *et al*. (2008) 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.

[9] 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).

[10] 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. Since the data in our study reflect ‘average behaviour’ (by size class, industry branch and country), individual firm's stochastic maximisation efforts are likely to be 'averaged out'. The associated type of endogeneity is therefore probably of limited relevance in the present study.

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

[12] Throughout this section 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).

[13] The average market share is the reciproque of the number of firms per data cell, normalised by the 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.

[14] The method of Battese and Coelli (1995) does not allow to take endogeneity of regressors into account.

[15] The calculation whether a data cell is subject to increasing, decreasing or constant returns to scale is based on solving a linear-programming problem for each observation.

[16] The fact that we use 'average' firms per data cell (country x industry x size class) as basic units of analysis imposes some limitations on the applicable econometric methods. If full micro data would have been available we would have controlled for firm-specific fixed effects (such as management quality) on the production and input choices that govern productivity outcomes. However, FE testing is not allowed, 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*. This is a form of selection effect that we cannot identify unfortunately, so that a control for firm-level fixed effects does not make sense.

However, we have made up for this by adding exogenous entry-exit rates for business services industry per country (source: Eurostat) to make up for the limitation in our data.

[17] 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.

[18] 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.