Being numerous does not yield efficiency - Productivity and entry-exit determinants in European business services

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Productivity and entry-exit determinants in European business services

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Abstract:

The paper investigates whether the poor productivity performance of the European business services industry is related to scale effects, market structure, and regulatory impacts. We apply parametric and nonparametric methods to estimate the productivity frontier and so obtain the distance of firms to the productivity frontier, using detailed industry-level panel data for 13 EU countries. Subsequently, we investigate how scale effects, market structure, and national regulation explain the distance with the productivity frontier. We find that that most scale advantages are exhausted after reaching a size of 20 employees. However, scale inefficiency is persistent over time, which suggests weak competitive selection. Market and regulation characteristics explain the persistence of X-inefficiency (sub-optimal productivity relative to the industry frontier). Entry and exit dynamics increase the productivity performance, while higher market concentration works out negatively. National regulatory differences also explain part of the productivity performance, especially if this affects exit behaviour and labour reallocation costs. The most efficient scale in European business services is achieved with close to 20 employees. Scale inefficiencies show a hump-shape pattern with strong potential scale-related productivity gains for the smallest firms, while the largest firms experience persistent scale-related diseconomies, suggesting that they operate in shielded monopolist markets. 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; scale efficiency; market selection; stochastic frontier model; non-parametric DEA analysis; entry-exit regulation; business services; European Union.

JEL codes: **D22, D24, L1, L5, L8**

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1 Introduction

During the past 30 years, the business services industry in most European Union (EU) countries has been among the industries with the highest growth pace. This held for its production, but even more for its employment growth. Business services industry nowadays forms a large part of EU economies as it already accounts for more than 10 per cent of total market-sector employment in the EU. It is also a major supplier of intermediary inputs to other industries. Its productivity record, however, is poor. Between 1979 and 2007, labour productivity barely increased. This productivity performance compares badly with the 1.9 per cent average annual labour productivity growth in the EU-15 countries in the same period. Moreover, labour productivity in the United States business services industry grew with yearly 0.7 per cent.[1]

The poor productivity performance of EU business services industry is puzzling. Large parts of this industry are knowledge-intensive, since it includes professions like consultants, accountants, engineers and computer experts. These people use to be innovative, often they advise other industries and therefore would be in an excellent position for delivering a good productivity performance of their own industry. The productivity record of the knowledge-intensive branches within European business services however differs hardly from the branches that have large employment share of low-skilled labour (Rubalcaba *et al.* 2007).

The low productivity growth is also reason for policy concern as it may negatively affect macroeconomic productivity growth (European Commission 2003). The industry is at risk of becoming a drag, both directly and indirectly, on the aggregate productivity growth of the EU. Directly, because business services represent a large part of total employment. Indirectly, because the business services industry is an important provider of intermediate inputs to other industries, and its low productivity may curb international cost competitiveness of downstream sectors too. Barone and Zingano (2008) find evidence for this negative downstream effect from productivity in professional services.[2] Antipi *et al.* (2010) decompose the European business services productivity gap vis-à-vis the USA. They conclude that input differences play only a minor role, but that the largest part of the gap is explained by the low European Total Factor Productivity (TFP) level, i.e. the residual factor in a production function that is typically associated with the functioning of markets and with institutional settings (regulations, business culture). It is on the operation of markets and regulation that we focus in our paper.

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[1] Antipi et al. (2010) find that business services in the USA contributed 0.1 percentage points to aggregate productivity growth in 1992-97 and 0.7 percentage points in 1997-2005. In France these figures were 0.0 and -0.1 points, in The Netherlands 0.0 and 0.1 points, in Germany -0.2 and -0.2 points, and in the United Kingdom 0.6 and 0.5 points.

[2] This impact on aggregate productivity may be counteracted by positive technological spillovers generated by several parts of business services industry, most notably the software industry. Evidence for such positive spillovers is found by, *inter alia*, Antonelli (1999), Hempell *et al.* (2002), Guerrieri *et al.* (2005), Kox (2004), Camacho *et al.* (2007), Baker *et al.*. (2008) and Van Leeuwen (2009). However, low productivity growth in business services may eventually erode such positive spillovers.

The paper investigates whether competition weaknesses or stringent regulations can explain the poor productivity performance of the European business services. With regard to competition we focus on the role of market selection through entry, exit, and the reallocation of market shares. In markets that select efficiently, firms with better, cheaper and/or innovative products will grow faster than firms with weaker performances on these issues. Firms with a persistently weak performance will shrink and eventually drop out. Market entry by new firms constantly feeds this selection process. The working hypothesis of this paper is that market structure, market selection efficiency and regulation can at least partly explain the poor productivity record of European business services industry.

To investigate this hypothesis, we proceed in two steps. Firstly, we estimate a productivity frontier per sub-sector and size class. This is done through a parametric model (stochastic frontier method) and a nonparametric model (data envelopment analysis). The different perspective from both approaches allows a deeper understanding of productivity and efficiency issues that play a role in different size classes of firms. Secondly, we explain the distance to the productivity frontier from market characteristics, entry- and exit dynamics and national regulatory features. We use panel data for 13 EU countries and eight industries of business services, covering the period 2000-2005.

The contribution of this paper to the literature is that - to our knowledge - it is the first productivity frontier study for European business services that integrates the analysis of scale efficiency, selection dynamics and regulatory obstacles. Also the combination of stochastic frontier and data envelopment analysis for this purpose is quite scarce in the literature. The vast body of studies has concentrated on manufacturing industries rather than, as we do, on services.

Our main findings are as follows. Firstly, we find that scale economies play an important role in business services. The overall efficiency pattern by firm size has a hump-shape form, with the minimum efficient scale being close to 20 employees and some further scale economies up to a size of 250 employees. Small firms with less than 10 employees – they represent 95% of all - have strong scale-related productivity disadvantages compared to the larger firms. This scale inefficiency is persistent over time. Secondly, we must reject the hypothesis that weak competition among the smallest firms is the cause of their scale-related productivity disadvantage. The smallest firms appear to operate in crowded market segments with much mutual competition, resulting in very similar production methods and similar productivity rates. This means that there is no general lack of competition for the small firms. Thirdly, European countries and industries with more market selection dynamics (as captured by national firm entry and exit rates) had less scale inefficiency. Fourthly, regulation-related obstacles to firm growth and market selection significantly explain firm distance to the production frontier and scale inefficiency. Countries with tougher regulation with regard to entry, exit and employment changes have significantly more scale inefficiency. Our overall finding is that market structure and regulatory regimes are important elements in explaining the poor productivity performance in European business services.

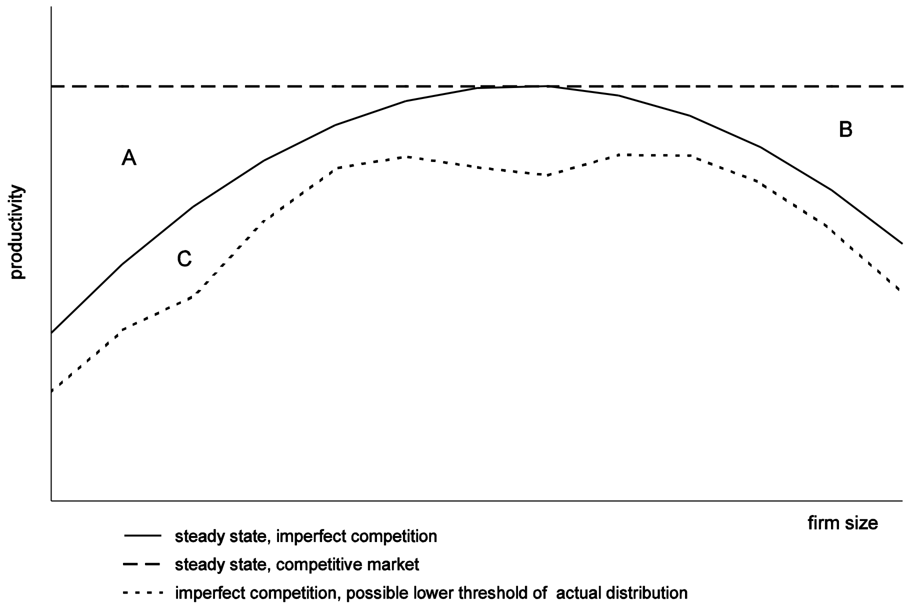
The structure of the paper is as follows. Section 2 develops the framework that we analyse from a brief literature review on the productivity determinants in services. Section 3 presents the empirical strategy based on the parametric and non-parametric frontier models, discussing in particular the flexible elements in the non-parametric DEA model that we will be using in the analysis of scale effects. Section 4 describes our data together with some descriptive statistics. Section 5 presents the results of the econometric tests. Section 6 summarises the main findings regarding the productivity determinants and it gives some possible implications for economic policy.

2 Related literature

This section gives a brief literature survey from which we develop the framework used in the rest of this paper. The main working hypothesis of this paper is that a imperfect competition may be an important candidate explaining the poor productivity record in EU business services. Factors that hamper dynamic market selection through entry, exit, shrinking and growing of market shares result in suboptimal market allocation. The invisible hand of allocative market re-ordering would otherwise ensure that the most productive, cheapest and most innovative producers are rewarded with higher market shares to the detriment of firms that under-perform in these respects (e.g. De Wit 2005; Arnold *et al.* 2008; Brown *et al.* 2008; Bartelsman *et al.* 2009). In a perfect market, scale economies would have no impact in the steady state, since all firms within an industry would have the optimal scale size. However, as soon as market imperfections play a role, scale starts to matter for the productivity of firms in an industry. Regulatory growth obstacles that cause discontinuities in the growth curve of firms may also hamper dynamic market selection and firm growth to the optimal scale size. Because of these elements, this section focuses on explanations offered by three explanatory factors from the literature: scale inefficiency, market structure issues, and regulatory barriers.

Returns to scale measures of the increase in output relative to a proportional increase in all inputs. Increasing returns to scale have a positive effect on labour productivity as output increases more than the labour input. Within an industry, scale economies may differ between firms depending on the technology they apply. In a competitive industry, one expects firms to grow in order to exploit increasing returns to scale. Figure 1 distinguishes three different relations between productivity and firm size. The first case (dashed line) is that of a fully competitive market; in the steady state there will only be firms of optimal scale, each of them exhausting the potential scale economies. The result is a straight line. The second case (uninterrupted line) is a market with barriers to market selection and firm growth. Not all firms will achieve the optimal scale and some firms will be too large with scale diseconomies. The result is a hump-shaped pattern of the productivity-size relation. The regions labelled A and B represent scale inefficiencies caused by market imperfections, with entry and growth barriers probably being most important in region A, while exit barriers and market power of incumbents are probably most important in zone B. The third case with the dotted line is the lower productivity boundary of a possible actual firm distribution in which no steady state has been achieved. The firms in zone C represent firms with sub-frontier productivity (X-inefficiencies) compared to the size-related frontier.

Figure 1 Relation between size and productivity in an industry with scale economies: steady state and actual distribution



Legend: The regions labelled A and B represent scale inefficiencies caused by market imperfections. The firms in zone C respresent firms with sub-frontier productivity (X-inefficiencies) compared to the size-related frontier.

Compared to manufacturing, scale economies in services are much less investigated, partly related to data availability problems (cf. Triplett *et al.* 2004; Diewert 2005). Scale effects in network services like transport, banking, payment services, retail distribution and telecommunication are reasonably documented (e.g. Schure *et al.* 1999; Bloch *et al.* 2001; Pels *et al*. 2003). Studies on scale economies in non-network services like business services are very scarce. Software producing services 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). Silk *et al.* (2003) find variable scale economies in advertising and marketing services. They conclude that scale efficiency gains are large at small size, but diminish sharply if firm size increases.

Competition may improve productivity through three channels: innovation, adoption and reallocation across firms of market shares and inputs (Nickell 1996; Aghion *et al.* 2005; Van der Wiel 2010; Cantner 2007). The first effect is already mentioned: competition stimulates market selection of firms. Competition causes forces inefficient firms out of business in the longer term; firms cannot survive and grow when their productivity is substantially less than the average for their industry. The permanent reordering of market shares raises aggregate productivity. A second effect is that more competition may generate innovations leading to higher productivity. Finally, competition may also stimulate firms to adopt best practices and in that way improving productivity. In terms of Figure 1, it will lead to a shrinking of the inefficiency zone C.

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. Empirical evidence for such dynamic productivity-related selection effects is well documented.[3] Due to entry-exit selection, firms with a productivity disadvantage compared to the industry's productivity frontier are not represented in the long-term 'steady-state' firm distribution (Olley *et al.* 1996; De Wit 2005). The same conclusion holds for markets with imperfect competition. In a world according to Dixit-Stiglitz (1977), where all firms have fixed set-up costs and constant marginal costs, each firm can offer its service variety in its own market niche. If consumers have a sufficient taste for variety, the market share of each service variety will be spread so thinly that the most inefficient producers have to drop out.

The persistence of inefficient firms (with low productivity) in a dynamic perspective is difficult to understand in a competitive industry with a homogeneous product. Inefficiencies could exist only temporarily. The persistence of inefficient firms is related to market power of incumbents and a lack of foreign competition due to fixed market-entry costs may lower domestic competition intensity and market selection in the business services industry. Incumbents with market power may use strategic barriers that increase entry costs and may deter entry. If free entry in a monopolistic services market is restricted, relatively inefficient producers may survive, lowering overall productivity performance (Kocsis *et al*. 2009). This may also give monopolistic firms the opportunity for tolerating X-inefficiency and refraining from innovation. Moreover, a lack of international openness of services markets prevents the exposure of inefficient firms to productive and innovative foreign challengers (CSES 2001; Copenhagen Economics 2005; Kox 2004, Kox and Lejour 2006; Nordås *et al*. 2009).

The impact of regulation can be such that it introduces fixed entry costs for new firms, causes post-entry growth obstacles and/or causes obstacles to downward flexibility (exit costs). Service markets have a long history of national government intervention, correcting for market failures such as externalities, asymmetric information, and market power in relation with economies of scale. These market failures occur in the production, distribution and consumption of services.[4] Because the production and consumption of service products often cannot be separated in place and time, these products are difficult to standardise, so that the

[3] E.g. Foster et al. (1998); Brown et al. (2006); Bartelsman et al. (2000, 2003, 2009); Ospina et al. (2010).

[4] When regulation successfully resolves market failures, it can reduce entry barriers and improve welfare, but not all measures successfully correct market failures. They may become growth and market obstacles in themselves.

quality of the services product is thus often *a priori* uncertain for the customer (Kox *et al. 2004*). Regulation in services markets may provide market power to incumbents, reduce incentives to innovate and prevents the entry of new firms. The literature shows that especially knowledge-intensive services are subject to several types of national regulatory measures (Paterson *et al.* 2003; Copenhagen Economics 2005; Kox *et al.* 2006; Baker *et al.* 2008). Product market regulation in business services may have a decelerating effect on the process of market share reallocation from less efficient to more efficient firms (Djankov *et al*. 2002; Nicoletti *et al*. 2003). Hence, lowering regulatory growth, exit and entry barriers may indirectly stimulate higher productivity, because it will strengthen competition.

Bartelsman *et al.* (2003) 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 the number of firms in industries with high entry than the US. Baker *et al.* (2008) conclude that the impact of stringent regulations regarding the types of activities that services providers can offer are reflected in the levels of concentration of national markets. Regulatory measures that regulate labour turnover and employment may affect the resource allocation and productivity performance of firms (cf. Jongen *et al.* 2010). Gust *et al.* (2002) show that more stringent labour market regulations affect a firm's decision to adopt new technologies, and lowers productivity improvements. Olley *et al.* (1996) have investigated market selection in the telecommunications during deregulation periods; they conclude that the deregulation waves went along with considerable intra-industry resource reallocation. Their results suggest that the breakdown of entry barriers apparently altered choices of (potential) producers, causing higher productivity growth through a reallocation of market shares, shift in vertical production chains, and an enlarged field of competitors.

3 Empirical strategy

We determine a productivity frontier in EU business services distinguishing between size classes, sub-sectors, countries and years. Once having determined the productivity frontier we test whether inefficiencies explain the incidence of sub-frontier productivities by size class. Subsequently, we investigate the impact of market and regulatory characteristics on the pattern of inefficiencies. We use two empirical models to conduct this analysis: a global stochastic frontier model (SF) with parametric features, and a non-parametric data envelopment analysis model (DEA). We make use of the different strengths of both models.

Stochastic Frontier Model. The SF model (e.g. Khumbhakar *et al.* 1991) is built around a translog production function. This model simultaneously identifies a parametric productivity frontier and it explains inefficiency using exogenous variables related to inefficiency. The availability of panel data enables us to apply the SF model of Battese and Coeli (1995) based on a translog production function that takes into account nonlinearities in the response of output to the scale of inputs.[5] We assume that the business services industry can be adequately described by a single output. Our starting point is a value-added production function, because this does not need restrictive separability assumptions on the underlying technology (Schreyer 2001; Diewert 2005).[6] We assume Hicks-neutral technological change, meaning that a change in technology does not change the ratio of capital's marginal product to labour's marginal product for a given capital to labour ratio. Hence, we ignore labour or capital augmenting technology.

The Battese-Coelli model assumes that the error term of the translog model consists of deterministic X-inefficiencies (τ), and a white-noise component μ. A second equation explains τ from a vector of exogenous variables. After rewriting the translog production function to obtain labour productivity as the dependent variable, the two-equation SF model to be estimated 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 equation (1), Y is value added in constan prices , K denotes physical capital inputs in constant prices, and L represents labour inputs. The parameters β_1 and β_2 reflect the linear effects of more inputs of capital and labour respectively 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 countries, industries, 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, industry and size class. Equation (2) assumes that mean sub-frontier inefficiencies (τ) depend deterministically on exogenous variables collected in **Z** and on random variation ('white noise'), represented by θ. Vector **Z** may include variables linked to competition issues. The random variable θ is defined by the truncation of the normal distribution with zero mean and variance σ_τ^2 with $-\gamma'\mathbf{Z}_{it}$ being the point of truncation.[7] Hence, $\theta_{it} \geq -\gamma'\mathbf{Z}_{it}$.

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5 We cannot use a cost function framework given the data (see section 4).

6 Since we have no data on intermediate inputs, we cannot use gross output production function. Point to assumptions + contra arguments: intermediate inputs are not that important in business services. Moreover, we use average industry data. problem of double counting when using gross output concept.

7 These assumptions are consistent with τ_{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).

The SF 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. Applying this method, we assume that a homogeneous technology holds for all size classes, industries, countries, and years. So, the technology parameters are equal for all firms, assuming the same technology; scale effects occur over the entire scale range. This means that frontier productivity can differ by firm size, industry, country and year as 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.

Although flexible, the SF model imposes a restrictive functional form and it needs specific assumptions concerning the distribution of efficiencies. The fitted SF technology gives an "average" or sample-wide estimate, which may not represent scale behaviour at lower levels. The SF model is therefore an adequate first approximation to detect sample-wide scale effects under the assumption that firms in all size classes apply the same technology. The SF model is less appropriate when technology differs across firm size, i.e. when technological or organisational discontinuities across size could be important. Moreover, a firm that is operating on the technological frontier may not be as productive as the frontier firms in other size classes may if scale efficiencies differ locally by size class. To deal with these possibilities we apply DEA.

DEA Model. DEA provides an alternative approach for investigating deviations from best practice related to competition issues. Moreover, the results of this model can serve as a robustness check on the SF results. The DEA method does not impose an a priori structure on inputs and output, whereas in the SF model the efficiency estimates are directly related to the model parameters (assumed to be unbiased). The DEA model also allows more flexibility by dropping the homogeneity assumption underlying the parametrically defined frontier allowing a deeper look into the nature of the scale effects. 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 'best-practice' we subsequently derive a set of X-efficiency measures and a direct measure of scale efficiency by size class allowing also for increasing or decreasing returns to scale. This approach circumvents the technological homogeneity assumption of the parametric SF approach. It also avoids the potential simultaneity biases related to the estimated parameters for the translog model. Having the relative efficiency scores of each firm, the sources of inefficiency can be further analysed.

DEA and 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 industry (j) and each year (t) a 'model free' 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 industry-specific frontier for each combination i of country and size class.[8] Using H as symbol for (average) productivity the VRTS X-efficiency indicator reads:

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

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:

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

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:

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

[8] 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).

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 SF 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

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 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 dataset 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 industry and firm-size detail. To allow full comparison across European countries we homogenise classifications at the lowest common denominator, thus sacrificing some available industry and size-class detail and data years in the data from some countries.[9] Homogenisation across countries yields a fully comparable set of data on business services industry in 13 EU countries, for eight industries and five size classes for the period 2000-2005. Ideally, we would then have 3120 observations at our disposal, but due to missings the number of data points amounts to 2362.

[9] 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.

Next we discuss the sources and the definition of our dependent variable and the explanatory variables respectively that we use for estimating the SF model and the DEA model. As central productivity index and dependent variable we use labour productivity, defined as real value added per employed full-time person derived from Eurostat's NewCronos database.[10] Value added is expressed in constant prices using the value added deflator per sub-sector of the business services industry from the EUKLEMS-database.

Regarding the production technology, we use depreciation as proxy for capital inputs and the number of employed persons as proxy for labour input. Both variables come from Eurostat's NewCronos database. Capital is expressed in constant prices using the gross output deflator per sub-sector of the business services industry from the EUKLEMS-database.

For characterising the market structure of the business services industries, we apply a combination of three indicators: average market size per firm, the Hirschmann-Herfindahl index (HHI) for concentration of market shares, and the average entry-exit rate of firms per market. The average market size per firm is calculated from Eurostat's NewCronos database 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 HHI stems from the EUKLEMS database and is defined in the usual way as the sum of the squared market shares of firms in a particular industry (O'Mahony *et al.* 2008). The industry is more concentrated the closer HHI is to 1. The average entry-exit rate of firms per market is an indicator for the intensity of market selection. It is calculated as the annual firm births minus annual firm deaths as a percentage of the number of active incumbent firms by country, industry and size class. Data for this indicator is derived from the business demography database from Eurostat. We expect a positive impact on productivity for the first and third indicator as they depict an increase in competition, whereas a higher HHI suggests less competition due to more concentration and, consequently, fewer incentives to increase efficiency or productivity. 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.[11] The four indicators are: (a) an

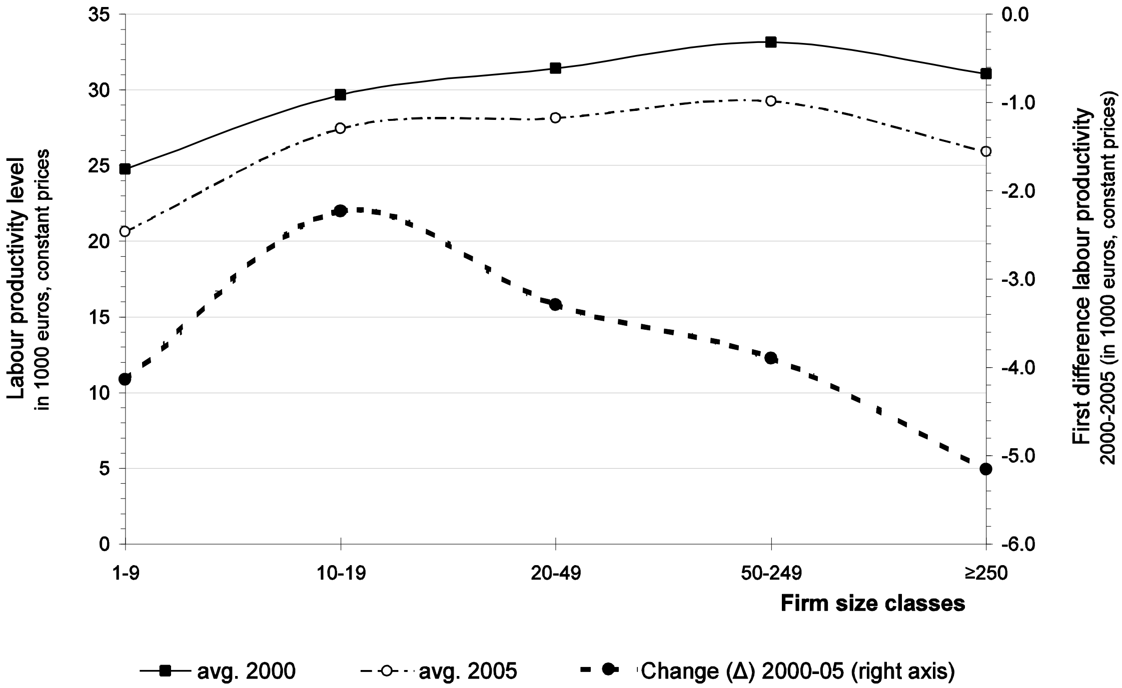
[10] The data would have allowed using TFP instead, but we have deliberately chosen not to use this measure. TFP is a non-explained residual from growth accounting, and as such a "measure of our ignorance" as Abramovitz already remarked in 1956. For TFP to be a correct measure of multi-factor productivity 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 the impact of these market conditions are precisely what we intend to investigate in this study, the use of TFP as productivity measure has to be ruled out.

[11] 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).

aggregate 'Cost of Doing Business' 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 and 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 four indicators it holds that a higher score represents more regulation-caused costs for firms. Based on the literature, we expect a negative impact of regulation intensity on both X-efficiency and on scale efficiency.[12] We present some descriptive statistics that underline the relevance of taking into account differences between size classes, sub-sectors and countries via dummies in our econometric specifications.

Figure 2 shows that the actual relation between productivity and size is not a straight line, as it would be in a competitive market (cf. Figure 1). 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 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, illustrating the poor productivity performance of this industry. The bottom curve in Figure 2 gives the first difference of average productivity by size class, suggesting that average productivity has diminished least in the size class with 10-19 employed persons. The graph only gives a first description, without correction for capital intensity or for composition differences (i.e. industry, country) in the averages for both years.

Figure 2 Average labour productivity by size class in total EU business services, average for 13 EU countries, 2000 and 2005



[12] These indicators are lagged one year in the estimations, which we assume to be a reasonable reaction time for firms on changes in this respect.

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 majority 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.

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 c) 2005	Cost of starting up a new firm d) 2005	Flexibility in employment contracts index e) 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 industries, 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 2 documents the variation in the dataset by industry dimension, showing that substantial differences exist. Productivity levels are highest in K720 (computer services) and K741 (legal, accounting, and consultancy services) across countries. These knowledge-intensive business services have higher productivity levels because they employ highly qualified workers with relatively high wage rates. Productivity levels are much lower in sub-sectors of the business services that produce more standardised services like K746 (industrial cleaning) and K747 (security services). The sub-sectors K745 (temporary labour intermediation), K746 and K747 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 (sluggish selection dynamics).

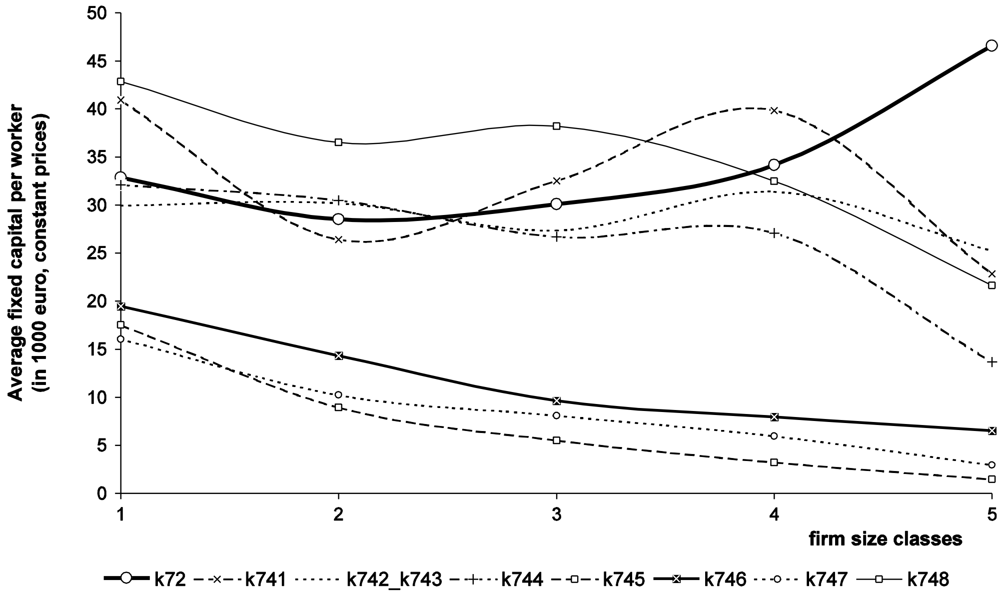
Table 2 Selected industry characteristics of the dataset, average for 13 EU countries, 2000-2005

Industry by NACE code [a)]	No. of data points	No. of firms covered (x1000)	Employment covered (x1000)	Productivity 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 concentration (HHI-index) [e)]	Average market share 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.

Figure 3 plots fixed-capital intensity per worker for the five different size classes for each industry. This confirms the indications from Table 2 about the differences in apparent scale economies between industries. Capital economies are about exhausted at a scale of 50 employed persons in temporary labour, cleaning and security services, whereas the picture in other industries 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 3 Capital intensity per employed worker, 2000-2005 average by industry



Note: industry codes are: K720 = 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

Table 3 presents the estimates of the SF model divided into two panels (A and B) and the results of two slightly different specifications of equation (2). Panel A shows the results of equation (1). Business services firms are – on average – characterized by increasing returns to scale. Taking into account nonlinearities in inputs, the overall score of the estimated technology parameters is a little above one.[13] The two 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 the input size of capital or labour respectively. Note that the results are obtained after controlling for frontier differences through dummies for industries, countries, size classes and years. Panel B of Table 3 presents the simultaneous estimates for equation (2) of the SF 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 or productivity.

[13] These 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.

Table 3 Estimates SF model, panel data 2000-2005

	Dependent variable: log(labour productivity)			
	(1)	(2)	(3)	(4)
	Estimate [a]	t-value	Estimate [a]	t-value
A) Translog-derived production function				
Technology variables:				
* Fixed capital	0.23***	11.3	0.24***	9.3
* Labour inputs	0.92***	18.5	0.96***	17.0
* Capital based local scale effects	− 0.05***	− 5.1	− 0.05***	−4.4
* Labour based local scale effects	− 0.12***	− 11.7	− 0.09***	−7.1
* Capital-labour interaction	0.05***	6.8	0.05***	4.7
Industry dummy included	yes		yes	
Country dummy included	yes		yes	
Size dummy included	yes		yes	
Year dummy included	yes		yes	
Constant	3.18***	56.8	2.80***	45.2
B) X-inefficiency equation				
Market structure variables:				
* Average market share per data cell	−0.04***	− 4.0	0.06***	2.7
* HHI	− 0.23	− 0.5	−0.04	−1.2
* Entry-exit			−0.11***	−3.7
Regulatory environment:				
* Overall Cost of Doing Business indicator	1.41***	6.6		
* Starting a business			0.55***	3.1
* Closing a business			1.24***	2.9
* Employment inflexibility			0.76	1.2
Size dummies included	yes		yes	
No. of observations	2362		1238	
Log Likelihood	−366.62		−133.26	

[a] Codes: * significant at 10% confidence level, ** significant 5% level, *** significant at 1% level.

In line with the predictions from the literature, higher regulation intensity according to aggregate 'Cost of Doing Business' indicator has a significant positive effect on X-inefficiency. 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. Columns (3) and (4) are based on a regression specification that decomposes specific regulation domains, to understand which regulation types matter most for productivity and scale economies in business services. 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). The results show that more regulatory obstacles for starting and closing a business increase the extent of X-inefficiencies.

Finally, the estimates in column (1) of Table 3 suggest that a larger average market share increases X-efficiency. This effect is counter-intuitive as fewer firms per data cell suggest more market power. 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 endogeneity of market shares.[14] Fiercer competition may force inefficient firms to leave the market. This increases the market share of efficient firms, and positively correlates with X-efficiency. In the specification reported in column (3), we control for entry/exit effects. We find a positive and significant impact of the average market share. Moreover, the coefficient of entry and exit is negative, indicating that market selection of firms has a positive effect on reducing X-inefficiencies as one would expect.

Using DEA as a robustness check for the SF results. This allows to look deeper into the issue of scale efficiency. Table 4 compares the X-efficiency predictions of the SF method with the X-efficiency measures derived from DEA (XE^{VRTS}, XE^{CRTS}). We recall that the DEA measures are calculated for every industry and year.

Table 4 Comparison of SF and DEA X-efficiencies, median for size class, 2000-2005

	Predicted efficiency SF model [a]	Calculated X-efficiencies on basis of DEA model [b]	
		XE^{VRT}	XE^{CRTS}
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

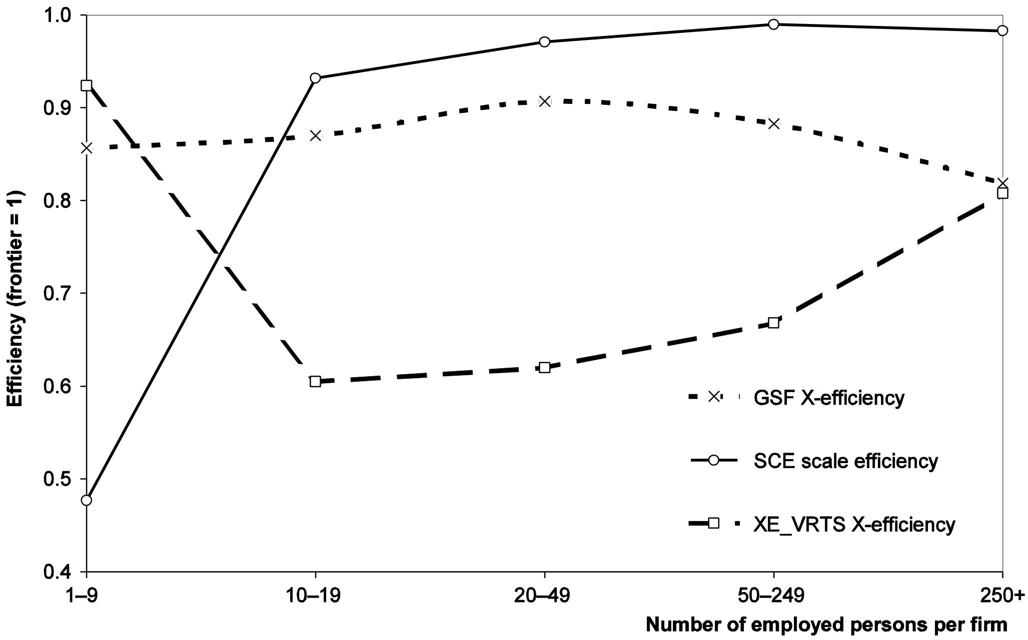
[a] X-inefficiency predictions on the basis of Battese-Coelli method calculated as $e^{-\tau}$ in order to be comparable with the DEA indicators. [b] X-efficiency indicator DEA allowing for variable returns to scale (XE^{VRTS}) or constant returns to scale . (XE^{CRTS})

The size of the XE^{VRTS} results is rather similar to the SF-predictions for the smallest and the largest size classes. However, for the other size classes, differences are more profound. This is not surprising, because a non-parametric variable-returns-to-scale frontier always envelops the data more tightly than a parametric method such as the SF model. Averaged over all observations, the SF model overestimates the X-efficiency in comparison to 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. The scale-efficiency indicator *SCE* (equation 5)

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

measures this.[15] Figure 4 jointly pictures the three most relevant efficiency indicators. The results are quite spectacular. The smallest size class has the highest degree of efficiency according to XE^{VRTS} (and about the SF average). It means that *within* this size class firms are close to the frontier.

Figure 4 Comparison of three efficiency indicators by size class (average all sub-sectors and countries, 2000-2005)



However, the SCE 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 size classes with 10-19 workers however has the lowest average X-efficiency, suggesting that within this size class there must be the largest deviation from the frontier 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 size classes appears to operate in

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15 As can be seen in equation (4) *SCE* 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. Annex I explains why this type of bias will be limited given the type of data that we use.

the increasing-returns-to-scale region (IRTS) of the production function, except for the size class of more than 250 employed persons. The results suggest that many small firms have the potential to increase their productivity by better use of returns to scale. Especially the potential scale gains of the smallest firms look quite sizable if they increase the number of employed persons or the amount of capital.

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

	increasing (IRTS)	decreasing (DRTS)	constant (CRTS)
Size classes:			
* 1–9 employed persons	97.0	0.6	2.3
* 10–19 employed persons	85.8	10.7	3.5
* 20–49 employed persons	80.4	15.0	4.6
* 50–249 employed persons	64.8	27.5	7.8
* ≥ 250 employed persons	26.0	55.0	19.0
All size classes	72.1	21.7	7.1

Explaining DEA inefficiencies. In a fully competitive industry, one would not expect inefficiencies to persist over time. Possible factors that could explain this are market-structure characteristics and regulation. We analyse this question with a Tobit regression model. Data limitations do not allow to 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.[16] Nonetheless, we may control for the intensity of entry-exit selection by adding exogenous entry-exit rates for business services industry per country as control variables. Like in Table 3 we zoom in on the possible role of specific regulation domains.

Table 6 reports the results for explaining DEA inefficiencies. It provides the marginal effects of a change in the explanatory variables in the conditional mean for DEA X-efficiencies and DEA scale efficiencies based on the random-effects Tobit models. As all continuous variables are expressed in logarithms, their estimated parameters can be interpreted as elasticities. Both the market structure and regulation variables in the columns (1) have a negative impact on X-efficiency as we would expect them to have. The regulation-caused entry costs, exit costs and employment inflexibility all have a significant negative impact on X-efficiency, with the largest effect coming from exit costs.

[16] 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. A firm that in year t is in size class 1 may or may not have grown into size class 2 at year t+x. The availability of full micro data would have allowed to control whether firm-specific fixed (FE) 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'.

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

	DEA X-efficiencies		DEA Scale efficiencies					
	$\log(XE^{VRTS})$		$\log(SCE)$		$\log(SCE)$		$\log(SCE)$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Estimated [c]	Z	Estimated [c]	Z	Estimated [c]	Z-value	Estimated [c]	Z-value
Size-class dummies:[a]								
* 10–19 employed persons	−0.507***	−12.5	0.623***	22.3	0.719***	19.3	0.696***	18.7
* 20–49 employed persons	−0.471***	−11.2	0.657***	22.7	0.755***	19.5	0.723***	18.5
* 50–249 employed persons	−0.405***	−9.0	0.655***	21.2	0.759***	18.2	0.715***	16.9
* ≥ 250 employed persons	−0.224***	−4.4	0.562***	16.1	0.665***	13.8	0.599***	12.0
Market structure:								
* Average market share	−0.005	−0.9	0.019***	5.1	0.015***	2.8	0.025***	4.4
* HHI	−0.023***	−3.7	−0.014***	−4.0	−0.013***	−2.0	−0.013***	−2.2
* Entry-exit					0.326***	2.3	0.316***	2.2
Regulation indices:								
* Overall Cost of Doing Business					−0.238***	−5.5		
* Starting a business	−0.140***	−6.8	−0.002	−0.2			0.01	0.6
* Closing a business	−0.211***	−3.1	−0.224***	−5.0			−0.313***	−3.0
* Employment inflexibility	−0.067***	−2.7	−0.057***	−3.6			−0.144***	−5.2
Industry dummies[b]	Yes		Yes		Yes		Yes	
No. of observations	2362		2362		1238		1238	
Log Likelihood	808.6		479.6		126.2		138.8	

[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) to (8) of Table 6 give the estimates for the model that explains DEA scale-efficiencies. Having a higher within-size class market share appears to increase scale efficiency. In line with our main hypothesis, we find that firms have to gain in market shares in order to capture scale economies. The strong impact of scale diseconomies in the smallest size class (as depicted in Figure 4) 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 4).[17] 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.[18]

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[17] An intuitive interpretation might be that a personal computer and small office are sufficient to start-up in many sub-sectors of the business services.

[18] 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 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.

So far, the regulation variables might pick up the intensity of entry-exit dynamics while regulation itself is not the 'culprit'. Therefore, we check whether the previous results remain stable after including a measure of entry-exit dynamics. We include this variable in the Tobit models for explaining DEA scale efficiencies. Columns (5) to (8) of table 6 present these results. We find a positive and significant parameter for the entry-exit variable. Higher net entry rates increase the incentive to gain in efficiency and this impact on efficiency turns out to be rather considerable. Entry-exit intensity apparently captures an additional competitive incentive separate from competition between incumbent firms. 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) due to missing observations for entry-exit rates, 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.

Testing for optimal scale size. Our data allow to test for the existence of an optimal scale of operation in business services, using the size-class dummies. The 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 use a constant term (not reported). Thus, the estimates for the size dummies 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). 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.

Table 7 Testing of differences between scale efficiencies of size classes

	SCE **(Table 6, column 3)**		***SCE*** **(Table 6, column 5)**		***SCE (*****Table 6, column 7)**	
	Estimated[a]	P value [b]	Estimated[a]	P value [b]	Estimated[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
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 $\chi 2(1)$ 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.

Table 7 presents the main results for testing for the optimal size using the DEA scale efficiency models. The first entry concerns the estimate for the difference between size class 2 (10 – 19 employed persons) and the reference group. In all three model specifications, 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 significantly different from zero, as can be inferred from the P-value of the 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 Wald test also takes into account the correlation between the errors of the estimates. 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 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 decreasing returns to scale for the largest firms.

6 Conclusions

Despite strong growth in terms of production and employment, the productivity growth track record of the business services industry in the EU 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. We have investigated the relationship between competition and labour productivity performance with a focus on scale inefficiency, imperfect entry-exit selection, and regulatory barriers that may hamper resource allocation to the most efficient firms. Doing so, we used both a parametric stochastic frontier (SF) model, and a non-parametric data-envelopment analysis (DEA) as a robustness check and as a method for further exploring scale efficiencies. After having established an industry-wise productivity frontier based on a large dataset for thirteen EU countries covering the period 2000-2005, we have calculated the distance to the productivity frontier and the incidence of scale inefficiencies. Subsequently, we tested whether and to what extent market structure and national regulatory differences explain the patterns in X-efficiency and scale efficiency.

The SF and DEA model come up with similar findings, and the estimates of these econometric techniques 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 with small X-inefficiencies (sub-optimal productivity relative to the frontier). 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 obstacles that hamper firms to grow and to exploit scale economies. Market and regulation characteristics explain the persistence of X-inefficiency and scale inefficiencies. 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 of this industry.

Overall we find that the most efficient scale in business services industry is up to a size of 10 to 250 employees and that scale inefficiencies show a hump-shape pattern with strong potential scale economies for the smallest firms and decreasing returns to scale for the largest firms. The smallest firms operate under competitive conditions, but they are too small to be productive. And since this conclusion holds for about 95 out of every 100 European business services firms, this factor weighs heavily against the overall productivity performance of the industry.

Our results suggest that future policies should reconsider measures that may hamper firm growth including regulation-caused obstacles to reallocate labour and close inefficient firms. If less stringent, these measures may have substantial positive effects on the productivity performance of EU business services. Several studies support this and show that less stringent regulation in services may also have positive knock-on effects in the rest of the economy (e.g. Arnold *et al.* 2008; Barone *et al.* 2008; Bourlès *et al.* 2010). They find that countries with less stringent service regulation have faster growth in value added, productivity, and exports by downstream service-intensive industries. Oulton (2001) has shown that the contribution of business services industry to aggregate growth may still be positive in case of small productivity gains, 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.

Demand for further study remains. For instance, this paper uses average firm level data per size class under the assumption that these observations can be considered as representative firms. Using firm level data for one country, further study could check this assumption. If this assumption has to be rejected, it strengthens the plea for a renewed focus on data availability (cf. Syverson 2010). Furthermore, the implementation of the European Services Directive in 2006 and its impact on the productivity performance of the EU business services industry also demand for further study. Finally, although integration of EU markets has been accomplished in many areas, comprehensive firm level data are still only available on a national basis from local statistical authorities. New challenges for productivity research arise if researchers could use linked firm level data across (EU) countries.

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 industries 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 industry 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 industries 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".[19]

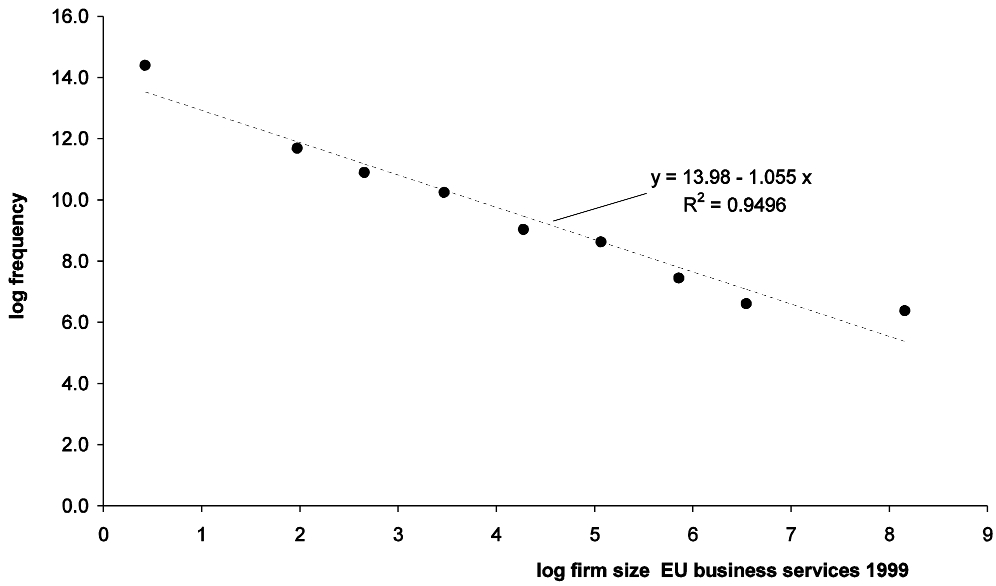
An important property of the Zipf-type Pareto distribution is that it is self-similar like a fractal, i.e. the distribution within size classes is similar to that prevailing over the entire size range. When we know the 'average' firm within a size class we indirectly know how this 'average' firm fits 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:

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

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

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 $\lambda_{i,j}$. 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.

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



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:

$$\begin{aligned} \hat{Y} &= Y + w_y \\ \hat{X} &= X + w_x \end{aligned} \tag{A3}$$

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

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