Measuring dynamic market selection by persistent scale inefficiencies - applied to EU business services

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Abstract:

The paper proposes a new way of analysing the efficiency of dynamic market selection, based on the persistence of scale economies. The persistence of scale-related inefficiencies is used as an indicator for the effectiveness of market selection.
We use a DEA method to construct the productivity frontier by sub-sector and size class, for business services in 13 EU countries. From this we derive scale economies and their development over time. Our results indicate malfunctioning competitive selection. Between 1999 and 2005 we observe a persistence of scale diseconomies, with scale efficiency falling rather than growing over time. In panel regressions we find the distance to the productivity frontier (within and between size classes) to be significantly explained by regulatory policies that hamper entry and exit dynamics and labour adjustment, and by a lack of import penetration and domestic start-ups. The results suggest that policy reform and more market openness may have positive productivity effects. This holds for business services itself, but also wider, because of business services' large role in intermediary production inputs.

Key words: market selection; scale economies; market contestability; regulation; EU

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

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1. Introduction

This paper explores a new methodology for comparing markets based on the effectiveness of competitive selection. The persistence of scale-related inefficiencies is used as indicator for the effectiveness of competitive selection. We apply the method to European business services, an industry that by now has a record due to its virtual productivity stagnation for more than a decade. We find ineffective competitive selection in large parts of European business services.The paper shows that this can be explained by a regulatory environment that protects incumbent firms and that hampers market dynamics, and by a lack of import penetration that otherwise would have contributed to more contestability of markets.

An efficient market ensures that more productive and innovative firms grow faster than others. Conversely, firms with weaker performance will be outcompeted and shrink or exit (e.g. Jovanovic 1982), with an intensivation during the down-swing phase of the business cycle (Aghion *et al.*, 1993; Ewijk, 1997; Caballero *et al*. 1994).[1] If markets are contestable by being open to potential hit-and-run entry, the incumbents have to keep a sharp eye on actual and potential competition (Baumol *et al*. 1982; Schwartz, 1986).[2] Entry by domestic start-ups and by foreign competitors with new and/or cheaper products feeds the competitive interaction. It forces the incumbents to present similarly priced products and innovations. Hence, new start-ups and import penetration may both promote the selection process by the market, as is also implied in the literature on international trade with heterogeneous firms (e.g. Melitz, 2003). Dynamic market selection necessarily goes along with shrinking or even exit of the least efficient firms. If regulatory policies create cost obstacles to employment adaptation and firm exit, this necessarily slows down the process of market selection.[3]

It is far from trivial to design an empirical indicator that measures market selection. It cannot be directly derived from productivity patterns of firms operating in the same market. The productivity pattern in an industry is affected by many factors: within the firm, in the market structure, and in wider setting in which the market functions. Bartelsman *et al.* (2000) mention the role of scale efficiency, management and ownership, the quality of the workforce and technology as possible explanations for productivity patterns in industries. We may add the regulatory environment to this list. Productivity may depend on factors that are external to the firm but do not affect all competing firms in similar ways. The multi-causality means that we cannot take the productivity distribution itself as an indicator of market efficiency. In this paper we have looked for firm characteristics that can be 'objectified' and still tell us something

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1 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.

2 Baumol et al. (1982: 5) define a perfectly contestable market as one that is accessible to potential entrants and has the following two properties. First, the potential entrants can, without restriction, serve the same market demands and use the same productive techniques as those available to the incumbent firms. Second, the potential entrants evaluate the profitability of entry at the incumbent firms' pre-entry prices.

3 Conversely, if regulatory policies themselves are the source of sunk market-entry cost this hampers market entry for domestic start-ups (Kessides, 1988; Djankov et al. 2002). The same is found to hold for regulatory heterogeneity that negatively affects foreign entry in EU services markets (Kox et al. 2006) and more generally in OECD services markets (Nordås *et al*. 2009).

about how the market functions. The incidence and persistence of scale-related efficiency gaps could serve as such an objectifiable characteristic. The advantage is that scale can be measured without knowing anything about management performance of firms or about the firm's environment.

We apply our methodology for evaluating the effectiveness of competitive selection to the European business services industry, a large industry that is responsible for 14-25% of total domestic value added in most of the older EU member states.[4] This industry has a productivity stagnation problem. Between 1980 and 2007, the business services industry booked a productivity growth that was in most countries zero or even below zero.[5] This industry had a zero or negative contribution to aggregate productivity growth in most of Europe.[6] The business services industry is the industry with the single largest contribution to Europe's productivity gap with the USA.[7] There may be further knock-on effects. Business services typically provides 15-20 per cent of all intermediary inputs.[8] The poor productivity performance of business services is therefore likely to contribute to future cost and competitiveness problems for its client industries.

What is behind this productivity stagnation? The jury is still out, but some evidence is available. Bartelsman *et al.* (2000) note that while entry and exit rates are fairly similar across industrial countries, post-entry performance differs noticeably between Europe and the United States. Post-entry growth in the EU is on average much slower in the EU and regulatory differences might partly explain this difference. Klapper *et al.* (2006) show that European countries with more costly entry regulations experience a slower growth of firms numbers in industries with high entry than the US. A number of studies argue that anti-competitive regulation can be the source of badly performing markets (Biatour et al. 2011; Bourlès et al., 2010; Buti and Deroose, 2010; Grilo et al., 2009; Arnold et al. 2008 and 2011; Nicoletti et al., 2003; Paterson et al., 2003). Regulatory entry barriers, a lack of import penetration and imported product varieties according to Ilkovitz et al. (2008) have a negative impact on market functioning in European business services. Especially knowledge-intensive business services are subject to several types of national regulatory measures. 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 (Baker *et al.* 2008). Costly regulations hamper the creation of new firms, create fixed costs and cause incumbent firms in otherwise high-entry industries to grow more slowly. 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) evaluate the effect of more

[4] Average for 2008 of all EU-15 countries except Greece and Portugal (OECD, 2011).

[5] Rubalcaba et al. (2007) show that between 1979 and 2003 the average annual productivity growth in European business services amounted to −0.3 per cent, against 1.6 per cent average productivity growth in the total European economy.

[6] Antipa et al. (2010) calculated that between 1992 and 2007 the annual contribution of business services to aggregate productivity growth was -0.24 percentage point in Germany, −0.03 in France, 0.1 in the Netherlands, 0.4 in the USA and 0.6 in the UK.

[7] Antipa et al. (2010); O'Mahony et al. (2010); van Ark et al. (2008).

[8] This refers to the share of domestically produced and imported business services in total use of intermediary inputs (domestically produced plus imported) in the total economy. In 2007, the share ranges from 11% in Spain to 28% in France, while Ireland is an outlier with 39%. Data are calculated from Eurostat input-output tables.

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. There is also evidence on the productivity stagnation in business services from another perspective. Growth-accounting studies found for business services a negative growth contribution of *total factor productivity* or TFP (O'Mahony et al., 2009; Jorgenson et al., 2005; Triplett et al., 2004). TFP is a residual factor that is, inter alia, associated with the functioning of markets and their institutional setting, but also with technological change (Hulten, 2001). Antipa et al. (2010) decompose the European business services productivity gap vis-à-vis the USA. They conclude that ICT use and input differences between the USA and the EU just play a minor role, but most of the gap is explained by *total factor productivity*, a result that is in line with the findings of O'Mahony et al. (2010).

This paper explores the operation of competitive market selection, using a new indicator that summarises the persistence of scale-related inefficiencies. The situation of European business services markets is a perfect case study. It is a large industry, with employment that is about as large as manufacturing. And moreover it is an industry that has a serious productivity problem.

The paper makes five novel contributions to the literature. Firstly, we develop this new indicator for the efficectiveness of market selection. It follows the idea that, in an efficient market, firms with scale diseconomies and consequent cost disadvantages cannot survive. If we find a pattern of persistent scale diseconomies, this must signal that competitive market selection is ineffective. Secondly, we estimate a productivity frontier for European business services (across countries) by industry, size class and year. The third contribution is that we assess the incidence of scale (dis)economies over time. We distinguish between efficiency gaps between and within size classes. Fourthly, we explain both scale efficiency and X-efficiency from structural factors like market contestability and regulatory characteristics. Finally, driven by constraints in internationally comparative data, we have developed a method of performing scale analysis on the basis of representative firms per data cell (industry by size class by country by year).

For the research we used a data panel for thirteen EU countries, covering the period 1999-2005, eight sectors of business services and five firm-size classes. Our main findings are as follows. We find an overall pattern of persistent scale inefficiency *between* size classes, though with considerable variation between countries and branches. Efficiency gaps *within* size classes (we label this X-inefficiency) are found to be persistent, and even increased in several countries during the observation period. Both findings points to weak competitive selection. The smallest size class[9] has a huge scale disadvantage relative to the most

[9] The size class with 1-9 employees represents more than 90 per cent of all business services firms in the EU and about one-third of total employment.

efficient size class, but its X-efficiency is much higher than within other size classes. It indicates that these smallest firms have very strong mutual competition, but apparently they are not in effective competition with firms of the larger size classes. The patterns of scale-related diseconomies within and between size classes are explained by market contestability (import penetration, start-up ratio of new firms) and by national regulatory policies. Focussing on the type of regulation, we find that X-efficiency and to a lesser extent also scale efficiency are hampered by regulation that creates disincentives to market entry, business closure and employment flexibility. Such regulation has in common that it disturbs the dynamics of competitive market selection.

The structure of the paper is as follows. Section 2 develops the framework for the analysis of competitive selection and market efficiency. Section 3 describes our methodology for identifying scale-related efficiency differences through primarily non-parametric data envelopment analysis. The section also presents the empirical data and the main patterns found in efficiency differences across countries, industries and size classes. Section 4 econometrically investigates the determinants of efficiency patterns in the EU (scale efficiency, X-efficiency). Section 5 concludes and draws some policy lessons. The annex describes and underpins our data strategy; it also provides descriptive information on the country and industry structure of the data.

2. A signalling device for weak market selection

In an efficient market we would expect that all firms try to operate on the scale size, because this is the size at which total profits are at their maximum. So, firms that are too small will try to grow because they are in a disadvantaged position relative to competitors at the optimal scale size. And the same holds for those firms that are too large; the latter will try to reduce their scale size. If not, they will be punished by the market, because standard market prices converge towards the level set by firms at optimal scale. Scale-inefficient firms experience lower profits and have to work harder to compensate their scale disadvantage or, otherwise, go broke eventually. Dixit and Stiglitz (1977) have shown that the competitive selection mechanism also operates in markets where monopolistic competition and market differentiation prevail. If the consumers have a sufficient taste for variety, not all scale effects will be fully exhausted in this Dixit-Stiglitz world, but a disciplinary market force remains in the form (actual or potential) entry of new competitors whose product variety competes for the same consumer budget. Given sufficient entry, the market share of each product variety will be spread so thinly that the most inefficient producers can no longer recover their marginal cost and drop out.[10] If free entry is restricted, relatively inefficient producers may survive in the market. Both in static and dynamic terms, this lowers productivity performance in that industry or market.

10 Several authors found empirical evidence for dynamic productivity-related selection effects (Foster et al. 1998; Brown et al. 2006) or endogenous exit behaviour and input decisions (Olley et al. 1996).

The implication of entry-exit selection in an efficient market 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). We take this steady-state firm distribution as a starting point for our framework of analysis. It is about a fictive industry in which scale economies are important. The productivity of firms systematically varies by size class because the latter have different technological, organisational or market-related options that affect productivity independently of management quality. For instance, small firms may be very flexible, but they have fewer possibilities for internal division of labour. Their employees are typically involved in multi-tasking, which has some productivity disadvantages (e.g. Coviello et al., 2010). Conversely, large firms may be good in splitting tasks and applying internal division of labour, but they become less flexible and have an imminent tendency towards bureaucracy. If a particular size class in an industry combines the best of both characteristics and gets the highest output from a given combination of inputs, we call it the optimal firm size. If its markets function well, all firms would eventually grow (or shrink) to the size at which scale advantages are best exploited. This optimal scale can be used as a benchmark.

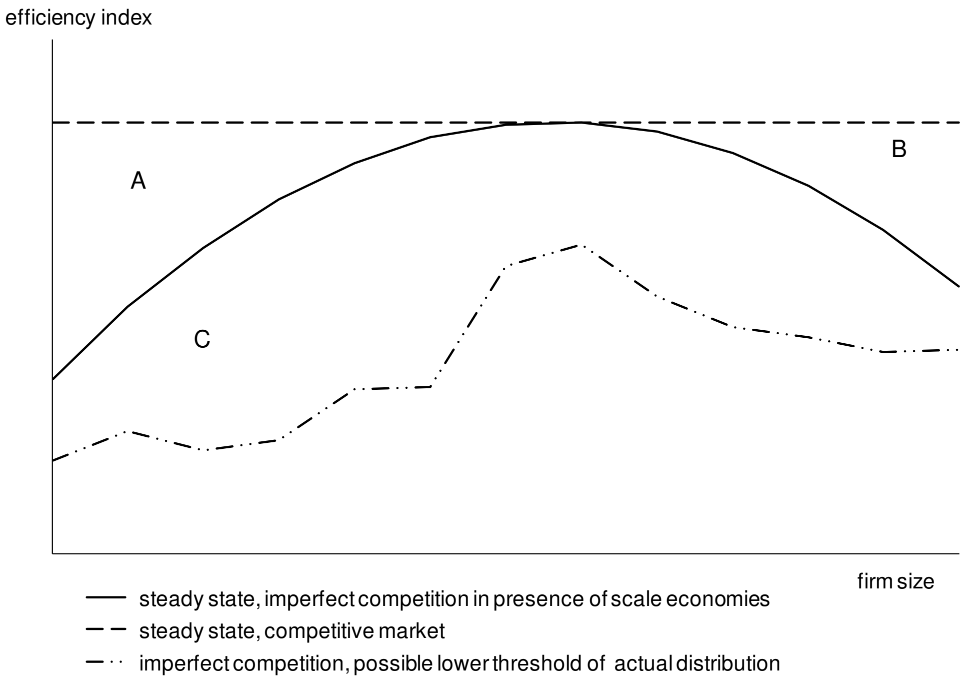
An intuitive version of our analytical framework is presented in Figure 1. The vertical axis depicts the productivity distribution of firms and the horizontal axis shows the firm population ranked by size at a given moment in time. The dashed line represents the "steady-state optimal scale". The smallest firms are found on the left side of the horizontal axis. The solid line depicts the productivity of the best-performing firms per size class if scale economies matter and competition is imperfect. Even the most-productive large and small firm are less efficient than the frontier firm with the optimal scale size. For the smallest firms this is caused by entry and or growth barriers in the market.[11] Such barriers are operative in area ***A***. The most-productive large firms on the right-hand side of the figure can hold their position despite the fact that they are less efficient than the firms with optimal scale size. Exit barriers and/or market power (area ***B***) relieve the pressure on them to shrink in size. Finally, probably a majority of firms operates less efficiently than the best-practice firms in their size class. The dot-dashed line in the graph depicts the position of the least-efficient firms in each size class. Area ***C*** between the solid and dot-dashed line represents the efficiency variation within each size class; it is labelled X-inefficiency.

If the analysis of Figure 1 is repeated at different moments in time, it provides a tool to distinguish between two kinds of weakness in market selection in an industry where scale economies are important. The first weakness is the persistence over time of scale inefficiency, i.e. competition fails to eradicate scale-related efficiency differences *between* size classes. This could be due to entry and growth barriers, market power and exit barriers (areas ***A+B***). The second competitive weakness is the persistence of X-inefficiency, i.e. market selection fails *within* size classes (area ***C***). The latter is not necessarily linked to scale

[11] Assuming a 'steady state' market situation in which all individual firms have completed their adaptation choices.

economies.[12] The crux of our methodology for detecting weak market selection is to assess the persistence over time of scale inefficiency and X-inefficiency. The shifts over time of X-inefficiencies and scale-inefficiencies provide the main information for evaluating the effectiveness of market selection.

Figure 1 Framework for analysing firm size, productivity and market selection



Our approach to measuring selection efficiency of markets is related to Boone's profits elasticity measure (Boone, 2004, 2008), but it may perform better if scale economies are important in an industry. The profits elasticity indicator is defined as "*the percentage fall in profits due to a percentage increase in marginal costs*" (Boone *et al*. 2007: 2). The underlying intuition of the profits elasticity indicator is that in a more competitive market, inefficient firms get punished more harshly in terms of profits. Boone's profits elasticity indicator measures how elastic a firm's profits are with respect to its marginal costs. The measure is not reliable with respect to size-related efficiency differences, because it is entirely focussed on marginal rather than average costs per unit. So it will miss any systematic relation between the level of marginal and firm size. It will overrate competition intensity in size classes with weak scale efficiency and high X-inefficiency (low profits). Conversely, it will underrate the competition intensity in size classes with high scale efficiency, where profits are relatively high. The eventual sign of the overall bias depends on the size relations between both parts of an industry. How important is this deficiency? Klette (1999) found that there may be more variation in market power and scale economies *within* an industry than *between* industries. Our indicator will probably be a more reliable proxy of competitive selection in industries where

[12] Possible reasons includes: a lack of local competitors (e.g. in rural areas), a lack of import competition, regulatory rigidities, strong product differentiation which makes each supplier a bit monopolist in its own product variety, information asymmetry, and search costs on the side of the clients.

scale economies are strong. This also includes several services industries like distribution, and business services.[13]

3. Productivity frontiers and the persistence of scale inefficiencies

A first step in operationalising our indicator for competitive selection is to estimate the productivity frontiers by business-services branch, size class and year. The non-parametric data-envelopment analysis (DEA) is a flexible approach that constructs an efficiency frontier in the relation between inputs and outputs. Individual firms, or 'decision-making units' (dmu) in DEA speech, are directly compared against a combination of peers. Since the method is non-parametric it does not impose an *a priori* functional form or weights structure on the relation between inputs and outputs. It can deal with multiple inputs and multiple outputs. The method calculates technical efficiencies without requiring product and factor price data as weights. This property is particularly useful for the analysis of productivity issues in services, since product price data in services are often weak. DEA can be used if inputs and outputs have different dimensions (e.g. number of employees, dollars of output).

The DEA method applies linear programming to construct a non-parametric piece-wise surface over the observed data for each meaningful grouping of firms.[14] The frontier is 'model free'; it is identified as the sample's 'best-practice' technology. It means that one needs a representative sample to get meaningful outcomes. The efficiency frontier either defines the maximum combinations of outputs that can be produced with a given set of inputs, or the minimum input combination that produces a given set of outputs. We use a DEA model that identifies the efficiency frontier associated with the minimum amount of inputs that can produce a given level of output (cf. Zhu, 2009).

Formal model[15]

Each dmu observation i ($i=1,...n$) uses m inputs x_{zi} ($z=1,..,m$) to produce q outputs y_{ri} ($r=1,...,q$). The efficiency frontier is derived from these n observations. Two properties of the dataset are required to ensure the feasibility and consistency of a piecewise linear approximation of the efficiency frontier and the area dominated by the frontier. The first property is convexity. Let $\sum_{i=1}^{n} \lambda_i x_{zi}$ $(z=1,...,m)$ be the possible inputs for each dmu i and $\sum_{i=1}^{n} \lambda_i y_{ri}$ $(r=1,...,q)$ the achievable outputs, where λ_i $(i=1,...,n)$ are non-negative scalars such that $\sum_{i=1}^{n} \lambda_i > 0$. Each λ_k ($k \in i$) weight parameter informs about the importance of observation/dmu k as reference dmu for dmu v. The second property is that inefficiency is allowed to

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13 Markusen (1989), Francois (1990) and Marrewijk et al. (1997) point out that most producer services are characterized by important scale economies. See further Shy (2001) on scale economies in IT industries.

14 See Cantner *et al.* (2007), Coelli *et al.* (2005) and Banker *et al.* (2004).

15 For expositional simplicity we briefly describe the general method. In the actual calculations we use a two-inputs (capital, labour) and one-output model. For multiple output/input cases, see Zhu (2009).

exist.[16] The input-oriented efficiency parameter Π_{zv} gives the factor by which inputs z of dmu v have to be multiplied to arrive at the same efficiency as the frontier firms. Hence, for the frontier firms it must hold that $\Pi_{zv} = 1$, and for the non-frontier $\Pi_{zv} \leq 1$. We start with a counterfactual analysis that will be used a framework of reference. The counterfactual analysis assumes that all firms and all size classes have access to the same technology as the best performing firm. It implies that if firms are less efficient, this can only be due to sub-optimal management decisions, i.e. by a 'wrong' combination of inputs. Because all firms have access to the same technology in this counter factual, it is a constant-returns-to-scale technology. The DEA model finds both λ_i and frontier efficiency Π_{zv}^{*crts} by solving the linear programming system:

$$\begin{cases} \text{target function: } \Pi_{zv}^{*crts} = \min(\Pi_{zv}^{crts}) \\ \textit{subject to}: \\ \sum_{i=1}^{n} \lambda_i x_{zi} \leq \Pi_{zv}^{crts} x_{zv} \qquad z = 1,...,m \;\; ; i = 1,...,n \, ; v \in i \\ \sum_{i=1}^{n} \lambda_i y_{ri} \geq y_{rv} \qquad r = 1,...,q \;\; ; i = 1,...,n \, ; \; v \in i \\ \sum_{i=1}^{n} \lambda_i > 0 \\ \lambda_i \geq 0 \end{cases} \tag{3.1}$$

with x_{zv} and y_{rv} representing, respectively, the z^{th} input and the r^{th} output for dmu v. Because of the DEA duality conditions, each input-oriented efficiency measure can also be expressed as an (output-oriented) measure of relative productivity, say h_{zv}^{rel}, the output per composite unit of inputs and relative to the frontier. For the set of frontier dmu Eff_i and the set of non-frontier dmu Ineff_i the following equivalence relations hold:

$$\begin{aligned} \mathit{Eff}_i &= \left\{ i \mid \Pi_i^{crts} = 1 \, , i = 1,...,n \right\} = \left\{ i \mid h_i^{rel} = 1 \, , i = 1,...,n \right\} \\ \mathit{Ineff}_i &= \left\{ i \mid \Pi_i^{crts} < 1 \, , i = 1,...,n \right\} = \left\{ i \mid h_i^{rel} < 1 \, , i = 1,...,n \right\} \end{aligned} \tag{3.2}$$

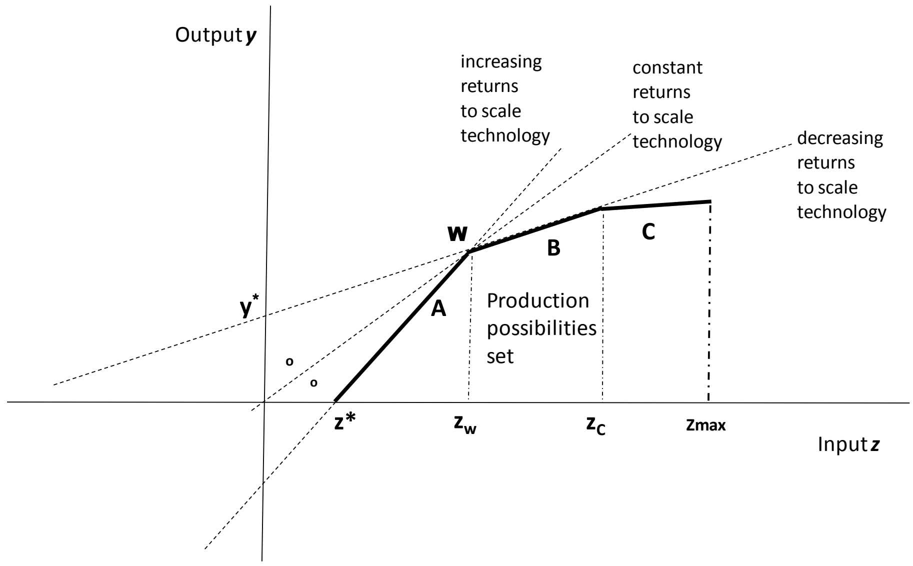
These results allow to derive the distance to the efficiency frontier, a continuous *in*efficiency measure:

$$DTF_i = 1 - \Pi_i^{crts} = 1 - h_i^{rel} \quad ; \quad 0\,(\textit{frontier}) \leq DTF_i < 1 \tag{3.3}$$

The constant-returns-to-scale (CRTS) analysis does not consider the possibility that there is a systematic relation between firm size and the amount of output yielded by a unit of inputs (scale economies). Figure 2 illustrates, however, how scale effects may affect the relation between inputs and outputs around evaluation point W. The dashed 45°-technology vector represents the case of constant returns to scale. The most horizontal, dashed technology vector represents the case of decreasing returns to scale that occur beyond output level y*. The other dashed technology vector depicts the case of increasing returns to scale technology, but this technology only yields positive outputs for input level z>z*. For (input-measured) firm sizes z<z* the increasing-returns-to-scale technology does not belong to the production possibilities

[16] The same y_{ri} may be produced by firms that use more inputs than the frontier firms. Alternatively, in an output-oriented envelopment model it is allowed that a common input quantity x_{zi} generates less output than is done by the frontier firms.

Figure 2 Production possibilities and input-measured firm size



set. For the input size range $\mathbf{z_w}$ - $\mathbf{z_{max}}$ the dmu cannot avoid the decreasing-returns-to-scale technology. The production technology may have discontinuities like at input sizes **z***, $\mathbf{z_w}$ and $\mathbf{z_C}$. The result is a kinked shape (ABC) of the production possibilities frontier and the production possibilities area dominated by the frontier. It has implications for the efficiency analysis. Firms below frontier part **A** should be compared with a dmu on frontier part **A**, and not with dmu on frontier part **B**, otherwise we mix up scale efficiency with 'technical' X-efficiency. While technical or X-efficiency may depend on short-term management decisions and demand conditions, scale efficiency is the result of longer-term firm growth, technology, and competitive selection in markets in which we are interested. DEA analysis allows to disentangle both types of efficiency. The sum condition $\sum_{i=1}^{n} \lambda_i > 0$ in equation system (3.1) affects the weights with which other, different-sized dmu enter the efficiency comparison for reference dmu *v* under a constant-returns-to-scale (CRTS) assumption. The more stringent sum condition $\sum_{i=1}^{n} \lambda_i = 1$ will force dmu *v* to be only compared with similar-sized other dmu. That allows to calculate variable-returns-to-scale (VRTS) efficiency parameters (e.g. Cantner et al. 2007). We thus set up a VRTS version of the linear programming problem to obtain a new set of λ weights and a set of Π_{zv}^{*vrts} efficiency parameters that *only* reflect X-efficiency, free of scale effects:

$$
\begin{cases}
\text{target function: } \Pi_{zv}^{*vrts} = \min(\Pi_{zv}^{vrts}) \\
\textit{subject to}: \\
\sum_{i=1}^{n} \lambda_i x_{zi} \leq \Pi_{zv}^{vrts} x_{zv} \qquad z = 1,...,m \;\; ; i = 1,...,n \, ; v \in i \\
\sum_{i=1}^{n} \lambda_i y_{ri} \geq y_{rv} \qquad r = 1,...,q \;\; ; i = 1,...,n \, ; \; v \in i \\
\sum_{i=1}^{n} \lambda_i = 1 \\
\lambda_i \geq 0
\end{cases}
\tag{3.4}
$$

Like for the CRTS parameters there is an equivalence with output-oriented efficiency parameters. The sets of, respectively, frontier and non-frontier dmu from an X-efficiency perspective are now:

$$
\begin{aligned}
Eff_i^{vrts} &= \left\{ i \mid \Pi_i^{vrts} = 1 \,,\, i = 1,...,n \right\} = \left\{ i \mid h_i^{rel,vrts} = 1 \,,\, i = 1,...,n \right\} \\
Ineff_i^{vrts} &= \left\{ i \mid \Pi_i^{vrts} < 1 \,,\, i = 1,...,n \right\} = \left\{ i \mid h_i^{rel,vrts} < 1 \,,\, i = 1,...,n \right\}
\end{aligned}
\tag{3.5}
$$

in which $h_i^{rel,vrts}$ are the (output-oriented) measures of relative productivity. After having identified the part of efficiency that stems strictly from X-efficiency, also scale efficiency can be derived for each dmu:[17]

$$
\Pi_i^{crts} = SCE_i \,.\, \Pi_i^{vrts} \;\Leftrightarrow\; SCE_i = \Pi_i^{crts} \big/ \Pi_i^{vrts} \quad ; \; 0 < SCE_i \leq 1 \, (\textit{frontier})
\tag{3.6}
$$

For the most productive firms in the most efficient size class it must hold that $\Pi_i^{*crts} = \Pi_i^{*vrts} = 1$, so firms in the global maximum have $SCE_i = 1$, while it is less than 1 in other size classes. Size classes are intervals and therefore contain more firms than the 'best practice' firms for which $SCE_i = 1$ holds. Empirically, the most-efficient scale size is the one for which average SCE_s is closest to one:[18]

$$
SCE_s^{frontier} = \max_s \left(\frac{1}{n_s} \sum_{i=1}^{n_s} SCE_{is} \right)
\tag{3.7}
$$

A few words are necessary to discuss possible limitations of DEA mentioned in the literature. Since DEA is an extreme-point technique that generates an envelope production function from real observations, problems could be caused by outliers, measurement errors and other noise. DEA indeed regards all deviations from the frontier as inefficiencies. In our case this problem should not be a big issue because our data points are representative firms per size class, which reduces the potential error from outliers and measurement error considerably.[19] DEA efficiency outcomes are also mentioned to converge slowly to the theoretical maximum efficiency. Again, this is not a problem for our analysis because we are not interested in theoretical performance, but in relative firm performance and in the way the market selects firms with a superior performance and 'punishes' those with an inferior performance. A final issue is that statistical hypothesis tests are difficult, since DEA is a nonparametric technique. We did use a parametric

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[17] Note that the CRTS and VRTS efficiency parameters are multiplicatively related, because in the input-output space both are measured on the same radius from the origin.

[18] Size classes may be ranked by their scale efficiency relative to that of $SCE^{frontier}$. The distribution may have several local maxima.

[19] The Data Annex discusses the potential effects of outliers and statistical noise at greater length..

stochastic frontier (SF) model as a robustness check, reported in Kox, Van Leeuwen, Van der Wiel (2010). This robustness check confirms that non-constant returns to scale dominate in the European business-services industry. Because of its very structure (uniform technology imposed on all size classes), the SF model is less flexible and less informative than the DEA method.

Data

Commercial databases with data on business services firms often have a systematic under-representation of small firms. Census data are still only available on a national basis from local statistical authorities, often under strict confidentiality conditions, which forms a severe handicap for internationally comparative studies. We solved the data problem by using Eurostat's NewCronos firm demography database as the basis for a new approach. Eurostat produces data on business services (sourced from national statistical offices) that cover many EU countries and the period 1995-2005. Each data cell provides information about a *country* $\times$ *industry* $\times$ *size class* combination: the number of firms, total sales, total value added, number of employed persons, and depreciation (proxy for fixed capital inputs). With these data we *construct* a representative firm (dmu) for every combination of *country* $\times$ *industry* $\times$ *size class*.[20] 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. The Annex deals with this data issue in more detail. The construction of the data base requires a few further decisions, because the national statistical offices until recently used to deliver statistical data on business services industry with different degrees of sector and firm-size detail. To allow full comparison across European countries we homogenise classifications at the lowest common denominator, thus sacrificing some available sub-sector and size-class detail and data years for some countries.[21] Homogenisation across countries yields a fully comparable set of data on business services industry in 13 EU countries, for eight sub-sectors, five size classes and for seven years (1999-2005). Theoretically this would yield 3640 observations on representative firms, but not all data cells are filled, and for most of the regressions we can use about 2700 observations. A further description of the data is found in the Annex.

The DEA efficiency indices reflect both labour productivity and the input of capital (depreciation) per unit of output. The data would have allowed using total factor productivity (TFP) instead, but we have deliberately chosen not to use this measure. TFP is a non-explained residual from growth accounting, and as such a "measure of our ignorance" (Abramovitz). 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

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20 Between 2000 and 2005, the data cover 2.5 million EU business services firms and 14.1 million employees.

21 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.

conditions (in the output market) are precisely what we intend to investigate with respect to business services, the use of TFP levels as productivity measure is out of the question. The DEA indices are probably superior to TFP, given the limitations of TFP as efficiency measure.

Descriptive results regarding scale inefficiencies

Table 1 provides the main efficiency scores for European business services, pooled over the period 1999-2005: general DEA efficiency (Π_{is}^{*crts}, CRTS), X-efficiency (Π_{is}^{*vrts}), and scale efficiency (SCE_{is}). The presented efficiency scores pertain to median observations per size class, but the underlying efficiency scores differ by industry and country. The efficiency scores display an interesting difference in the efficiency patterns for X-efficiency and scale efficiency.. Size class 1 has a higher X-efficiency than any other size class. It means that firms *within* this size class apply nearly the same technology, with hardly any distance between the frontier firms and the average firm. It signals that *within* this size class there must be strong competition that eradicates or punishes efficiency slack. On the contrary, the efficiency slack in the size classes 2, 3 and 4 amounts to 34-39%. This can indicate that the competitive pressure to converge towards the best-practice way of running a business is quite weak within these size classes.

Table 1 Efficiency scores by size class, across sectors, countries and years (1999-2005), medians by size class[a)]

Size classes	CRTS efficiency [b)]	Scale efficiency	X-efficiency (VRTS)
1 (1–9 employed persons)	0.42	0.49	0.93
2 (10–19 employed persons)	0.57	0.93	0.61
3 (20–49 employed persons)	0.60	0.97	0.62
4 (50–249 employed persons)	0.65	0.99	0.66
5 (≥250 employed persons)	0.70	0.98	0.81

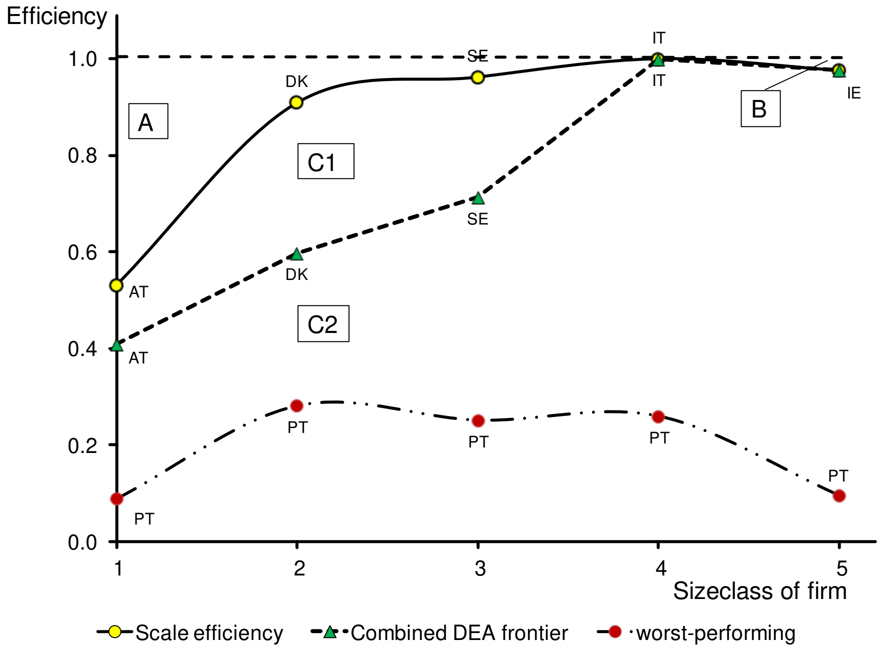
[a)] The average number of scale indices per size class is 591, of which the median value is presented. [b)] Calculated as median DEA CRTS efficiency (=scale efficiency times X-efficiency). Source: own calculations.

When we compare the scale efficiency differences *between* the size classes a completely different picture arises. The scale-efficiency scores show that −from a productivity perspective− the technology of the smallest size class is grossly sub-optimal compared to the other size classes. The scale efficiency of size class 1 is less than half that of the most efficient size class (4). Hence, size class 1 has significant diseconomies of scale. The median scale efficiency jumps up to above 90% once a firm passes the 10-employees threshold , and after that, increases only marginally, reaching a top in size class 4 (50-249 workers). Scale efficiency falls slightly in the largest size class, hinting at some diseconomies of large scale. However, the difference is small and could fall within a measurement-error range. However, there is additional evidence on this item.

Firms operating on a sub-optimal scale may be found on the increasing-returns-to-scale part of the production function. This can be explored by calculating for each data cell whether it is subject to increasing, decreasing or constant returns to scale (cf. Kox, Van Leeuwen and van der Wiel, 2010). The vast majority of the observations is found to operate in the increasing-returns-to-scale region of the production function. A considerable number of cases operates in the decreasing-returns-to-scale region, especially in the larger size classes. The distribution of the marginal DEA-scale efficiencies thus permits the conclusion that many small firms have the potential to increase their productivity by a better use of scale economies. Firms in the smallest size class have a large potential for scale-related productivity gains if they would succeed in growing to a size of 50-249 employees. The latter size class (4) can be considered as the optimal size class on the basis of Table 1. Once a firm has reached a size of 20-49 employees its potential scale-related efficiency gains have diminished sharply (to 3%). The absolute firm growth required to get from size class 1 (1-9 employees) to size class 2 is quite small, but the scale-efficiency results nonetheless suggest that such firm growth would be highly effective for average productivity in European business services. We recall that the smallest size class represents 95 of all firms and one-third of total employment in European business services.

The results so far were presented at an aggregated level. To get a better flavour of the results at the level of the individual business-services branches, Figure 3 shows the distribution of size-related efficiencies for the Architectural, engineering, technical services branch in 2005. The only variation left in this graph is the variation between countries. The presentation is similar to the analytical framework depicted in Figure 1, but now with real data.

Figure 3 Scale performance in Architectural, Engineering & Technical Services (K742-3), per size class, 2005



Note: AT =Austria; DK=Denmark; SE=Sweden; IT=Italy; IE=Ireland; PT=Portugal.

It shows that the countries on the SCE-frontier differ by size class (Austria, Denmark, Sweden Italy and Ireland), and that Portugal is consistently the worst performer. The X-inefficiency area ***C*** of Figure 1 is now split in two parts: area ***C1*** shows the X-inefficiency for the countries that are at the scale-efficiency frontier (by size class), while area ***C2*** shows the X-inefficiency area for all other countries. Especially the ***C2*** X-inefficiency area shows the wide dispersion of productivity performance within this European business-services branch. We have suppressed the data points for other countries, to avoid that the graph becomes too cluttered. Size class 4 (50-249 employees) is the optimal size class for the EU countries as a whole, but this is not necessarily the case in individual countries. For instance in Portugal's architecture and engineering industry, size class 2 appears to be the most productive one.

We propose to measure competitive selection over time by the persistence of scale- and X-efficiencies. Data is available for the time interval 1999-2005. This was a period of strong growth for EU business-services industry in which dynamic reallocation of market shares could have generated a convergence towards an optimal scale of operations or towards reduction of X-inefficiencies. Table 2 shows for eight industries whether scale efficiency and X-efficiency between 1999 and 2005 went up or down, or stayed the same. The data cells with improving scale efficiency formed the majority in four industries (IT services, labour recruitment, industrial cleaning and miscellaneous business services), whereas for X-efficiency the 'improvers' formed the majority in three industries only (K72, K744 and K748). Improvers formed the majority for both scale-efficiency and for X-efficiency in only two industries (IT services, and miscellaneous business services). Conversely, two industries (K741 and K742-3) experienced a deterioration of both types of efficiency.

Table 2 Change in DEA efficiencies, by EU business-services industry, 1999-2005

Industry	Change in X-efficiency (no. of observations) [a]			Change in scale efficiency (no. of observations) [a]		
	diminish	zero	increase	diminish	zero	increase
K72 (IT services)	97	18	170	136	2	147
K741 (Legal, audit, accountancy, consultancy)	197	15	147	300	0	59
K742-3 (Architectural, engineering, technical)	332	33	50	398	0	17
K744 (Marketing services)	55	9	245	205	0	104
K745 (Labour recruitment and selection)	130	47	160	134	8	195
K746 (Industrial cleaning)	137	35	140	113	8	191
K747 (Security services)	128	47	170	197	11	137
K748 (Miscellaneous business services)	46	17	271	60	2	272
Total observations	1122	221	1353	1543	31	1122

[a] Change between 1999 (or closest available starting year) and 2005 (or closest available final year). The variation in the data is by country and size class. Source: own calculations. Source: own calculations.

Table 3 repeats this analysis at the country level. X-efficiency has has 'nett' improved in six countries (Austria, Belgium, Spain, France, Sweden and the UK), whereas a positive change in scale efficiency only prevailed in France. Elsewhere, the scale efficiency and X-efficiency have worsened or remained the same. The results so far show that weak scale performance is a wide-ranged phenomenon that cannot be ascribed to a few countries or a particular industry.

Table 3 Change in DEA efficiencies, by country, 1999-2005

Industry	Change in X-efficiency (no. of observations) a)			Change in scale efficiency (no. of observations) a)		
	diminish	zero	increase	diminish	zero	increase
Austria (AT)	90	22	116	143	8	77
Belgium (BE)	74	18	130	131	6	85
Germany (DE)	138	0	102	132	0	108
Denmark (DK)	65	10	55	86	1	43
Spain (ES)	60	8	92	84	0	76
Finland (FI)	48	14	41	65	6	32
France (FR)	84	14	182	126	7	147
Ireland (IE)	56	9	61	63	3	60
Italy (IT)	154	28	98	182	0	98
Netherlands (NL)	93	55	112	154	0	106
Portugal (PT)	102	6	103	123	0	88
Sweden (SE)	82	19	140	130	0	111
United Kingdom (UK)	76	18	121	124	0	91
Total observations	1122	221	1353	1543	31	1122

a) Change between 1999 (or closest available starting year) and 2005 (or closest available final year). The variation in the data is by industry and size class. Source: own calculations.

In a further breakdown of the results, Table 4 displays that improvements of X-efficiency were concentrated in the three smallest size classes, with the relatively strongest improvement in size class 1. The X-efficiency performance of the largest size classes generally has worsened over time. Scale efficiency on average has worsened in all size classes except in the size class with 50-249 employees. Not only the number of cases with increasing or decreasing efficiency matters, but it also matters what happened with the width of the efficiency gap between the most- and least-efficient size classes. In a competitive industry we would expect that this gap diminishes over time due to dynamic selection.

Table 4 Persistence of scale performance in EU business services by size class, 1999-2005

Size class	Change in X-efficiency (no. of observations) a)			Change in scale efficiency (no. of observations) a)		
	diminish	zero	increase	diminish	zero	increase
1 (1–9 employed persons)	159	94	303	338	9	209
2 (10–19 employed persons)	262	7	281	345	0	205
3 (20–49 employed persons)	235	1	314	326	1	223
4 (50–249 employed persons)	266	12	259	257	5	275
5 (≥250 employed persons)	200	107	196	277	16	210
All size classes	1122	221	1353	1543	31	1122

a) Change between 1999 (or closest available starting year) and 2005 (or closest available final year). The variation in the data is by country and industry. Source: own calculations.

Table 5 shows by country that this process does not occur. Only in France the observations with a shrinking scale-efficiency gap outnumbered the cases with a growing or constant scale-efficiency gap. It could mean that scale economies have become more important, but we found no positive evidence for that in the form of increasing capital-labour ratios. We therefore conclude that convergence to an optimal scale is not imposed by market forces in European business services. Rather than that, competition *between* size classes has weakened in in most countries. The average X-efficiency gap *within* size classes became larger or remained the same in most countries, but diminished in Austria, Belgium, Spain, France, Sweden and the UK.

Table 5 Change in average efficiency gaps, by country over time interval 1999-2005

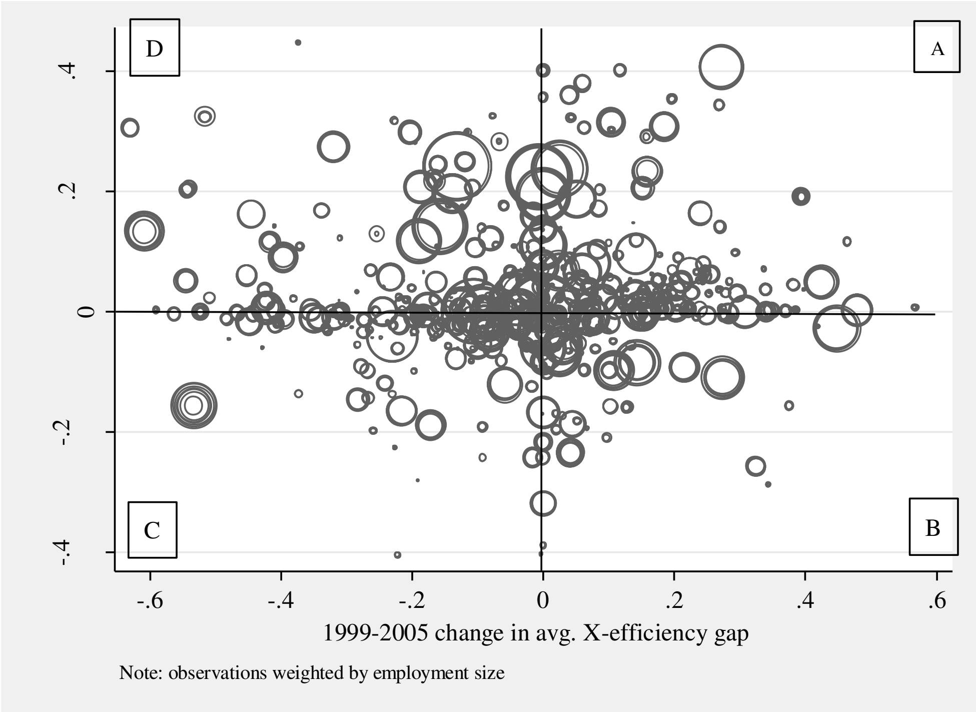
Country	Change in average X-efficiency gap (no. of observations) [a)]		Change in average scale-efficiency gap (no. of observations) [a)]	
	Diminish	Same or larger	Diminish	Same or larger
Austria (AT)	116	112	77	151
Belgium (BE)	130	92	85	137
Germany (DE)	102	138	108	132
Denmark (DK)	55	75	43	87
Spain (ES)	92	68	76	84
Finland (FI)	41	62	32	71
France (FR)	182	98	147	133
Ireland (IE)	61	65	60	66
Italy (IT)	98	182	98	182
Netherlands (NL)	112	148	106	154
Portugal (PT)	103	108	88	123
Sweden (SE)	140	101	111	130
United Kingdom (UK)	121	94	91	124
Total observations	1353	1343	1122	1574

[a)] Change between 1999 (or closest available starting year) and 2005 (or closest available final year). The variation in the data is by industry and size class. Source: own calculations.

Not all data cells are equally important in terms of employment. Figure 4 is a scatter plot of the employment-weighted change in the average size of efficiency gaps within and between size classes. The size of the dots is proportional to the employment size of each data cell. In a dynamic market with effective competitive selection we would expect a reduction in both efficiency gaps, with a clear dominance of observations in the southwest quadrant C. This is not what we observe in Figure 4. Many heavy-weight dots are found in northwest quadrant D (smaller X-efficiency gap, but larger scale efficiency-gap) and in northeast quadrant A (increase of both efficiency gaps). The pattern is not driven by outliers, but is found in parts of European business services that represent large chunks of overall employment. A short characterisation of the dynamic pattern is that we observe an overall increase of scale-efficiency gaps with a mixed performance regarding X-efficiency gaps.

Wrapping up, most of the descriptive results point towards poorly behaving market selection in European business services. Firms with scale-inefficiency where not penalised by market selection, which points to low competition intensity between size classes. For competition within size classes we find at best a mixed pattern. Our micro-based evidence could solve the puzzle of negative TFP-growth performance that was found in several growth-accounting studies for EU business services (cf. section 1): weak and even weakening market selection may have caused the unexplained negative TFP-growth.

Figure 4 Change in average efficiency gaps over 1999-2005 interval , observations weighted by employment size



4. Explaining scale-related inefficiencies

Since we find divergent results for different countries and industries, the next challenge is to identify the market characteristics and environment factors that explain the dynamics of scale-related inefficiencies. Our preferred approach is a Tobit model in which X-efficiency and scale efficiency are explained as continuous variables in a panel data context for 1999-2005. We do several robustness checks to investigate the stability and soundness of the Tobit results.

The hypothesis that we test is that regulatory characteristics and market contestability variables explain the level of scale-efficiency and X-efficiency per data cell.[22] The data has a panel structure, holding information on both the intertemporal dynamics and on the observed group entities. It allows to deal efficiently with unobserved or missing variables. A Tobit regression is applied because of the continuous but censored nature of the DEA variables (cf. Hsiao 2006). We apply a random-effects Tobit panel estimator, which accounts for the possibility that our selection of countries and industries has impact on the results. An additional reason to apply random effects (RE) relates to the structure of our data. Though we know the number of firms in each data cell, we do not know which firm is in what data cell in which year.[23] This limitation rules out the use of a model with firm-level fixed-effects, but a RE model is a good stand-in. We test two similar Tobit panel regression models for explaining the scale efficiency and X-efficiency performance, for explaining the scale efficiency and X-efficiency performance, respectively SCE_{sjkt} and Π^{*VRTS}_{sjkt}:

$$\begin{aligned} \ln(SCE_{kjst}) &= \psi\,\mathbf{M}_{kjst} + \varphi\,\mathbf{R}_{kjt} + \alpha_1\,\mathbf{z}_s + \alpha_2\,\mathbf{z}_j + \upsilon_{kjst} \\ \ln(\Pi^{*VRTS}_{kjst}) &= \beta\,\mathbf{M}_{kjst} + \lambda\,\mathbf{R}_{kjt} + \delta_1\,\mathbf{z}_s + \delta_2\,\mathbf{z}_j + \mu_{kjst} \end{aligned} \tag{4.1}$$

in which $\mathbf{z}_j$ and $\mathbf{z}_s$ are vectors of fixed-effect dummy variables for, respectively, industries and size classes; the **M** vector collects explanatory variables for market contestability, the **R** vector contains variables for the regulatory environment, and υ_{sjkt} and μ_{sjkt} represent error terms.

As explanatory variables for the regulatory environment our first model applies an umbrella indicator, and in a second model we differentiate to three regulatory variables for specific domains of entry , exit and labour-adjustment costs. The umbrella indicator *regulation-caused costs of doing business* (*cdb_aba*) varies by country and year is constructed from the least aggregated data of the World Bank Cost of Doing Business database. *cdb_aba* is a combined index based on 46 quantitative sub-indicators for regulation-linked costs for ten business activity areas, like starting a business, getting credit, enforcement of contracts, closing a business, employing labour, getting licenses, getting credit, trading across borders

[22] Recall that our observations are constructed representative firms per data cell (unique combinations of size class, industry, country and year), which is the lowest level of data detail for which we have internationally comparative data.

[23] We cannot identify whether individual firms move between size classes, e.g. whether 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 or, for that matter, whether it has completely exited.

and paying taxes.[24] A higher value on this index reflects more business costs. In our second model we use indicators from the same World Bank source and with the same properties, but now for regulation in specific business areas that affect dynamic market selection. For entry costs we use the *cost of starting a business* index, for the regulatory costs of hiring and firing workers and flexibility in labour contracts we use *employment inflexibility*, and for exit costs we use *costs of closing a business*. To avoid possible multicollinearity problems between *employment inflexibility* and *cost of starting a business*, we have interacted *employment inflexibility* with each data cell's capital-labour ratio. Based on the literature (section 1), our hypothesis is that all four regulatory variables have a negative impact on both scale efficiency, X-efficiency, and the persistence of both, because the regulation tends to shield-off the incumbent firms. The **M** vector holds variables for the contestability of national business services markets. Since the persistence of scale diseconomies is used as an indicator for competitive market selection we cannot use any market structure variables like market concentration ratios that are *outcomes* of competitive selection. Instead, we use two variables that proxy the (exogenous) contestability of the incumbents' market. The first one is import penetration, measured as the share of imports in total domestic use of business services.[25] The second one is the start-up rate of new firms.[26] Both imports and start-ups may have two discernible competitive impacts:

a. they potentially contest the market position of national incumbent firms by introducing innovation, new varieties, cheaper products and new marketing methods.
b. they may exert a 'business stealing effect' with a potential threat to the rents of the incumbent firms, and/or the market share and scale gains of the latter.

Foreign firms generally bring with them some scale advantages, built up in home markets or elsewhere. For import penetration it is not a priori evident how this works out for X-efficiency and scale efficiency. More import penetration probably induces more X-efficiency, but not necessarily more scale efficiency. The 'business stealing' effect could undermine the achievement of scale gains by domestic firms. Domestic start-ups increase domestic market contestability for incumbent firms, because of their actual and potential 'business stealing' effect. We test these two market variables first separately and then in combination. A problem is that the number of observation drops by almost one-quarter if we include the domestic start-up ratio, due to missing data.

Table 6 provides the marginal effects of a change in the explanatory variables in the conditional mean of, respectively, DEA X-efficiencies and DEA scale efficiencies, both calculated on the basis of the

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[24] The index is constructed by item-wise comparing each EU country with a 60-country reference group in which all 28 sub-indices for individual business areas enter the umbrella index with equal weights. It varies in the [0,3] space.

[25] Calculated from annual national input-output tables, as provided by Eurostat. Because Ireland is an outlier for import penetration ratios (much higher than average, possibly a 'Microsoft' effect), we add a specific country dummy for Ireland in all regressions where import penetration is an explanatory variable.

[26] Defined as the number of new firms by data cell over the number of incumbent firms, using data from the Eurostat business demography database, with variation by country, industry and year. In case of missing data we proxied the variable as the net growth rate of the number of firms per data cell $\Delta nof_{kjst} / nof_{kjst-1}$, even though this proxy is like to understate the real annual start-up rate, because of non-observed exits.

random-effects Tobit models. All continuous variables are expressed in logarithms. The results may be read as elasticities, giving the x% change in the conditional mean of the DEA scale efficiencies or X-efficiencies after 1% change in an explanatory variable. In both tested models, all regulatory variables have a significant negative impact on X-efficiency, with the largest effect (-0.3) for the *costs of closing a business* and the regulation-linked *employment inflexibility* index (-0.12). Import penetration has a significant positive impact on X-efficiency. When turning to scale efficiency, all regulatory variables still have a negative sign, but the regulatory *costs of starting a new business* appears not to have a significant impact. Also import penetration has no significant impact on scale efficiency. Domestic start-up ratios in none of the regressions have a significant impact.

Table 6 Explaining scale efficiency and X-efficiency performance, using Tobit panel estimator with random effects, 1999-2005 (13 countries, 8 industries, 5 size classes)

	Scale efficiency: $\log(SCE_{kjst})$		**X-efficiency**: $\log(\Pi^{*VRTS}_{kjst})$	
	Model 1 [c)]	**Model 2** [c)]	**Model 1** [c)]	**Model 2** [c)]
Regulatory environment:		**<preferred>**		**<preferred>**
* Umbrella indicator cdb_aba (log)	− 0.082 *** (0.023)		− 0.144 *** (0.040)	
* Starting a business (log)		− 0.005 (0.010)		− 0.082 *** (0.024)
* Employment inflexibility (log)		− 0.048 *** (0.014)		−0.129 *** (0.016)
* Closing a business (log)		−0.148 *** (0.039)		−0.306 *** (0.049)
Market contestability:				
* Import penetration (log)	-0.019 (0.016)	0.006 (0.017)	0.078*** (0.023)	0.096 *** (0.029)
* Start-up ratio (log)		0.001 (0.007)		− 0.006 (0.007)
Size-class dummies: [a)]	Yes	Yes	Yes	Yes
Industry dummies [b)]	Yes	Yes	Yes	Yes
Ireland dummy [d)]	Yes	Yes	Yes	Yes
No. of groups	499	491	499	491
Avg. no. of observations per group	5.4	4.2	5.4	4.2
Total no. of observations	2696	2063	2696	2063
Wald chi2	577.2 ***	1116.9 ***	486.8 ***	548.6 ***
Log likelihood fitted model	595.9	400.0	−920.2	-676.7

[a)] Benchmark is the smallest size class with 1-9 employed persons. [b)] Benchmark is the computer services industry (K720). [c)] The figures between between parentheses are bootstrapped standard errors derived by 50 replications of the regressions for each of the groups reported in the table. *** indicates statistical significance at the 1% confidence level based on Z values. [d)] A dummy for Ireland is applied because of its exceptionally high import penetration.. Source: own calculations.

To investigate the role of unobserved country heterogeneity we did also a OLS regression on the same dependent variables using the same explanatory variables, but with standard errors clustered by country. This reproduced the same pattern of estimated parameter values and statistical significance as in Table 6. The only major difference was that import penetration was no longer significant, possibly due to the fact that (because lacking detailed data) we had to measure import penetration at the national level for business services as a whole, where it may be correlated with other non-observed country heterogeneity.

Because the random-effects Tobit model is relatively sensitive to regression errors that are not normally distributed we used a bootstrap procedure for deriving reliable standard errors. This robustness check changed the results only marginally. Table 6 presents the ‘bootstrapped’ results. As a robustness check we have replicated the ‘Model 2’ regressions in Table 6 for individual business-services industries to obtain a better understanding of what drives the aggregate results. Moreover, in order to rule out the possibility that our results are mainly driven by the large scale-efficiency gap of the smallest size class (1-9 employees), we have also run separate regressions for the smallest size class and the pooled other size size classes.

Table 7 presents the main disaggregated results.[27] Although there are differences at the level of industry and size group it shows that regulation-linked *employment inflexibility* and *costs of closing a business* have a significant negative impact on both the scale efficiency and the X-efficiency of almost all industries and for both size groups. Regulatory start-up costs for domestic entrants have a small negative impact on X-efficiency in almost all industries, while their impact on scale efficiency is in many cases slightly positive.[28]

Import penetration has a positive impact on X-efficiency in most industries, although the lack of industry-level import penetration data may have limited the number of cases where this variable is statistically significant. Import penetration tends to have a small negative impact on scale efficiency, hinting at the importance of the ‘business-stealing’ effect.

The differences between the regression results for the “1-9 employees” size group and the “10+ employees” size group are small enough to reject the hypothesis that the results of Table 6 are mostly driven by the smallest size class. For one item we see a remarkable differences between both size groups. While for the larger size groups regulatory employment inflexibility only has a statistically significant negative impact on *X-efficiency*, for the smaller size group the (statistically significant) negative impact arises almost exclusively with respect to *scale efficiency*. For the smallest size class the attainment of scale efficiency is apparently hindered by regulatory employment-related growth obstacles.[29]

[27] Since import penetration penetration at the level of individual industries are not available we proxy this variable by the import penetration level for business services at the country level. The other variables are the same as in Table 6, except that we left out the start-up ratio variable. Otherwise this variable would (due to missings) limit the number of observations which is already lower at this desaggregated level.

[28] The latter might be taken as an indication that ‘business-stealing’effects from more entry have non-negligible impact on incumbents, thus making it more difficult for them to attain scale efficiency.

[29] A similar effect was recently found for France by Garricano. Lelarge and Van Reenen (2012)

Table 7 Industry-level explanation of scale efficiency and X-efficiency performance, estimated elasticities from Tobit RE panel estimator (1999-2005, 13 countries, by size group)

Industry	Size-class specifica-tion	Dependent variable: X-efficiency				Dependent variable: Scale efficiency			
		Regulation Starting a business (log)	Regulation employment inflexibility (log)	Regulation closing a business (log)	Import penetration (log)	Regulation Starting a business (log)	Regulation employment inflexibility (log)	Regulation closing a business (log)	Import penetration (log)
All industries	All sizes	-0.05**	-0.09***	-0.24***	+0.08***	-0.00	-0.05***	-0.07***	-0.01
	>10 empl	-0.06***	-0.09***	-0.26***	+0.08***	+0.01*	-0.02***	-0.03***	-0.00
	1-9 empl	-0.01	-0.10***	-0.12***	+0.07*	-0.05	-0.15***	-0.23***	-0.04
Computer and IT services	All sizes	-0.09*	-0.11***	-0.39***	+0.05	-0.02	-0.04	-0.17***	-0.01
	>10 empl	-0.09**	-0.09***	-0.49***	+0.01	-0.01	+0.00	+0.00	+0.00
	1-9 empl	-0.06	-0.15	-0.08	+0.10	+0.01	-0.15	-0.44***	-0.01
Accountancy, legal serv., managem. consultancy	All sizes	-0.03	-0.11**	-0.20***	+0.05	+0.01	-0.07***	-0.08***	-0.04
	>10 empl	-0.02	-0.13***	-0.22***	+0.01	+0.00	-0.02	-0.05***	-0.01
	1-9 empl	-0.03	-0.07	-0.14***	+0.16*	+0.00	-0.21	-0.25***	-0.14
Architectural & engineer-ing services	All sizes	-0.06*	-0.16***	-0.19***	-0.04	-0.03	-0.04	-0.02	-0.03
	>10 empl	-0.06*	-0.17***	-0.20***	-0.03	-0.02*	-0.00	+0.00	-0.01
	1-9 empl	-0.06	-0.14	-0.11**	-0.10	-0.09	-0.12	-0.19	-0.04
Marketing services	All sizes	-0.12*	-0.02	-0.36***	+0.03	+0.01	-0.06*	-0.10***	-0.04
	>10 empl	-0.13**	-0.01	-0.40***	-0.02	+0.03	-0.03	-0.05***	+0.01
	1-9 empl	-0.08	-0.03	-0.11*	+0.10	+0.00	-0.22**	-0.39***	-0.16
Labour recruitment services	All sizes	+0.13**	-0.13*	-0.33***	+0.20***	+0.04	-0.07*	-0.14***	-0.03
	>10 empl	+0.07	-0.10	-0.41***	+0.16**	+0.02	-0.03	-0.02	+0.02
	1-9 empl	+0.34***	-0.31	-0.09	+0.28	-0.04	-0.10	-0.36***	-0.13
Industrial cleaning	All sizes	-0.04	-0.18***	-0.18***	+0.11***	+0.02	-0.11***	-0.07***	+0.03
	>10 empl	-0.03	-0.18***	-0.21***	+0.17***	+0.03	-0.02	-0.04***	-0.02
	1-9 empl	-0.05	-0.10	-0.07*	-0.08	+0.02	-0.44***	-0.17	+0.20
Security services	All sizes	-0.04	-0.13**	-0.29***	+0.19***	+0.01	+004	+0.01	-0.01
	>10 empl	-0.05	-0.16**	-0.31***	+0.20**	+0.00	+0.00	-0.00	-0.01
	1-9 empl	+0.06	-0.01	-0.17***	+0.15	+0.06	-0.24	+0.03	-0.05
Miscellan-eous busin. services	All sizes	-0.11**	-0.02	-0.24***	+0.06	-0.03	-0.01	-0.08***	-0.00
	>10 empl	-0.11*	-0.06	-0.27***	+0.05	+0.00	+0.01	-0.03**	-0.00
	1-9 empl	-0.08	-0.05	-0.07	+0.13*	-0.12	-0.01	-0.21***	-0.05

Legend: Table presents estimated elasticities from RE Tobit panel estimator by industry specification and size group. With fixed effects by year and by size class (not in case of the regressions for smallest size class 1-9 employed persons). The asterisks denote the statistical confidence derived from the *z* values: * at 10%, ** at 5% and *** at the 1% level. The number of observations by industry is the same as the number of observations by industry in Table 2. Source: own calculations.

5. Conclusions

This paper has investigated the efficiency of competitive market selection, using the persistence over time of scale-related inefficiencies (within and between size classes) as key indicators. The scale inefficiencies have been derived by DEA methods. The method has been applied to analyse market performance in European business services. Most countries during the period 1999-2005 display a persistence and even deterioration of scale inefficiencies (between size classes), while the picture for X-inefficiencies (within-size class efficiency gaps) was mixed at best. This signalling device gives strong indications that EU markets for business services are only weakly selective. Scale-related inefficiencies appear to be persistent and they point towards weak competition *between* size classes. The most salient finding is that small firms appear to compete mostly with other small firms, but not with firms in other size classes. Similarly, in many countries and industries we also find weak competitive selection *within* size classes of the same industry. Our results appear not to be driven by a few countries or size classes, but prevail widely in European business services.[30] The pattern of weak dynamic market selection may explain the results by other studies that European business services industry has zero or even negative TFP growth over the past decades.

Which factors may explain the variation between countries and industries in the persistence of scale-related inefficiencies? To find out we did panel regressions with two market-contestability variables (domestic start-up ratios, import penetration) and four regulation variables that pertain to the entry costs, exit costs and employment-adjustment costs. The regulatory variables all have a significant negative impact on X-efficiency, and most of them also have a negative impact on scale efficiency. Import penetration has a significant positive effect on within-sizeclass competitive selection, but was found not to have a significant impact on scale efficiency (perhaps due to ‘business stealing’ effect which makes the attainment of scale gains more difficult). We have replicated the same type of analysis at the industry level, which grosso modo confirmed the results of the pooled panel regression. Regulation-linked *employment inflexibility* and *costs of closing a business* have a significant negative impact on both the scale efficiency and the X-efficiency of almost all industries. On the basis of further decomposition we can reject the hypothesis that our results are mainly driven by the performance of small firms.

Business services firms supply 15-25% of all intermediary production inputs in the EU countries. Weak competitive selection in such a key industry may be of more than academic relevance. Our conclusions are relevant for current European policies, such as ‘Europe 2020’, that aim inter alia at more integration of European services markets. While business services imports tend to increase the number of product varieties available for domestic firms, our results indicate that more import penetration also improves dynamic market selection. Another conclusion is that regulatory reform is important. Especially regulation that lowers exit costs (*costs of closing a business*), regulation that makes labour adjustment by firms more flexible, and regulation that lowers start-up costs for new firms could strengthen dynamic market selection and, indirectly, the productivity performance. Supplementary research is required to asses the extent to which entry, exit and labour-adjustment costs are industry-specific.[31]

ANNEX ON DATA

A. Data on the representative firm by 'data cell'. 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

[30] From an industry perspective, the strongest market-functioning problems were found in two large business-services industries: (a) accountancy, legal, administrative and consultancy services, and (b) architectural and engineering services. The situation was better *but not very much* better in: IT and computer services; labour recruitment services; industrial cleaning; and in security services.

[31] In 2012 or 2013 the OECD will publish a set of detailed regulatory indicators per services industry and per country (Services Trade Restrictiveness Index, or STRI). This could yield a fruitful input for such supplementary research.

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 equals:

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

with λ_o being the minimum firm size and α the shape parameter of the distribution. For firms the minimum size is one employed person. Axtell found that for US business the shape parameter (α) had the value of *1.059*. This implies that the relation between the log of frequency and the log of firm size can be described as a straight, downward-sloping line, i.e. the distribution is extremely skew. This result appeared to be robust when using other firm-size measures such as turnover (Axtell 2001, 2006). The Eurostat data on the EU business services include the total numbers of firms in each size class, thus allowing to implement the same test on firm-size distribution properties that Axtell did. The first test aggregates the data for all sub-sectors of business services and 11 EU countries in 1999. The result –shown in Figure A1– is very 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".[32]

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:

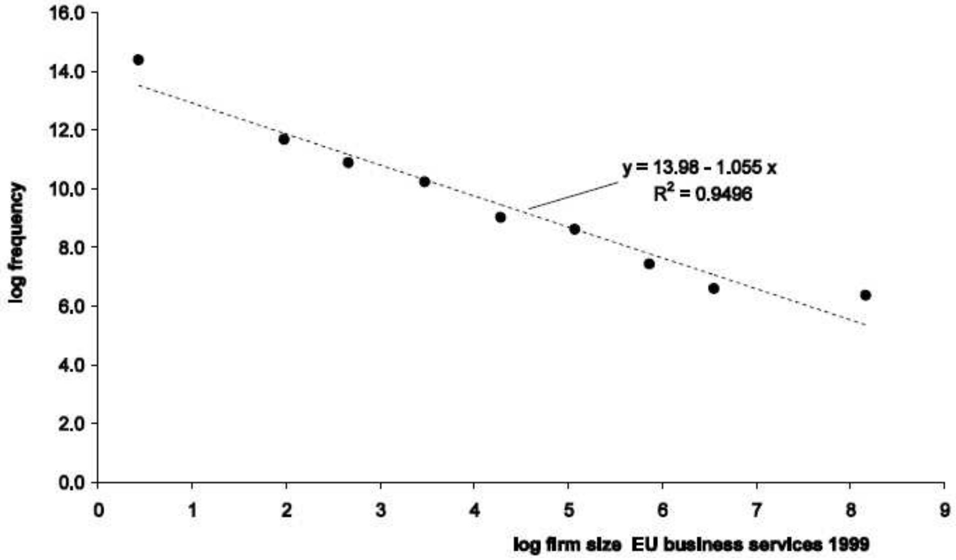
$$\Pr\left[MIN_j \leq \lambda_{i,j} < MAX_j\right] = \int_{MIN_j}^{MAX_j} f(\lambda_{i,j})\, d\lambda_{i,j} = \left(\frac{MIN_j}{\lambda_{i,j}}\right)^{\alpha} \tag{A2}$$

with $\lambda_{i,j}$ being the size of "average" firm *i* in size class *j* (cf. Johnson *et al.* 1994: 208; Axtell 2006). The implication of property (A2) is that once we have identified the "average" firm $\lambda_{i,j}$ we also have some information on the firms that within the size class distribution are located at the left and right of firm $\lambda_{i,j}$. With respect to scale effects, this property allows to derive in a stochastic sense some conclusions on a marginal change of firm size, so that standard scale analysis can be applied with regard to our dataset.

B. Representative firms and accuracy of the DEA method. The fact that we do not have data available on real firms (dmu) 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.

32 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.

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



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:

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

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

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

C. Explanatory Variables. Regarding production technology, we use depreciation as proxy for fixed-capital inputs and for the number of employed persons as proxy for labour input. labour input. Both variables come from Eurostat's NewCronos firm demography database. For market contestability we use import penetration (business services imports as percentage of apparent domestic us of business services), calculated from Eurostat's standardised input-output tables by year. Data on domestic start-up rates (new firm as % of the number of incumbent firms) are derived from the Eurostat SBS panel and from EUKLEMS data administered by GGDC at Groningen University. Missing start-up data have been constructed from the Eurostat New Cronos database for business services. Data for the national regulatory environment of business services firms have been 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.[33] The four indicators are: (a) an overall index based on 28 sub-indices for policy-caused business costs; (b) an exit-costs indicator for the regulation-caused costs of closing a business; (c) an indicator for the costs of setting up a registering a new firm; and (d) an indicator for the degree of inflexibility in employment contracts, representing national differences in costs for labour reallocation, hiring and firing. For each of these for indicators it holds that a higher score represents more regulation-caused costs for firms. The correlation matrix for the regulation variables shows that a joint use of some regulation indicators could cause multicollinearity. For that reason we have interacted '*Cost of Closing a Business*' with the capital-labour ratio per observation.

Table A1 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:		Overall cost of doing business [d] 2005	Cost of starting up a new firm [e] 2005	Flexibility in employment contracts index 2005
					total no. of firms	total employ-ment			
Austria	196	42	243	28.4	91.3	35.6	0.76	0.61	0.69
Belgium	184	76	386	33.8	95.7	28.5	0.69	0.61	0.62
Denmark	96	16	108	37.6	91.4	24.6	0.55	0.19	0.20
Finland	98	16	81	33.2	94.1	33.6	0.67	0.25	1.09
France	240	399	2684	29.7	93.5	24.2	0.79	0.26	1.40
Germany	240	344	3242	28.6	87.0	23.0	0.84	0.60	1.34
Ireland	103	11	70	34.4	91.5	36.4	0.65	0.38	0.50
Italy	240	739	2059	28.0	97.5	53.0	1.08	0.66	0.83
Netherlands	230	104	677	42.1	91.7	24.8	0.80	0.53	1.02
Portugal	193	60	281	12.6	96.2	37.0	1.12	1.06	1.56
Spain	160	378	1918	18.9	95.2	34.7	1.12	1.01	1.54
Sweden	207	141	453	30.4	96.7	43.2	0.80	0.25	0.96
Un.Kingdom	175	426	3234	44.0	91.2	26.8	0.44	0.34	0.29
Total	2362	2751	15436						
Average	182	212	1187	30.9	93.3	30.9	0.79	0.52	0.93

a) Productivity level as value added per employed person (in 1000 Euros, constant prices), average for all business services branches, 2000-2005. b) Share of firms with less than 10 employed persons. c) Composite indicator of regulation-caused cost of doing business (0 is lowest level), relative to a 60-country sample, based on 28 sub indicators in Cost of Doing Business database (cf. Nordås *et al.* 2009: Annex II). d) Relative regulation-related costs of starting up a new firm (0 is lowest level), relative to a 60-country sample, based on 3 sub indicators 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 sub indicators 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: Nordås *et al.* 2009).

D. Some descriptive statistics. Table A1 presents descriptive statistics on the country variation in the data set. With on average 182 data cells per country we have 2,362 observations for the period 2000-2005,

[33] 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.

covering 2.8 million EU business services firms with 15.4 million employed persons.[34] Business services typically forms a small-scale industry. The overwhelming share of firms has less than ten employed persons. Italy, Portugal and Sweden have the largest share of firms with less than ten employed persons. In terms of their share in total employment, the smallest size class accounts inmost countries for 25-33% with again Italy and Sweden being the exceptions. The average productivity differs considerably between countries, though industry composition effects and country differences in average income also play a role here. Average productivity is highest in Netherlands and the UK, and lowest in Italy and Portugal. The table also displays country scores with respect to three regulatory variables that we use. Table A2 documents variation by the industry dimension, showing that substantial differences exist between the 3-digit sub-sectors. The sub-sectors K745 (temporary labour intermediation), K746 (industrial cleaning) and K747 (security services) display a distinctly larger average firm size than the rest of the sub-sectors. This difference in apparent scale economies is mirrored in a significantly lower amount of fixed capital per worker between these three sub-sectors and the rest of them. Table A2 shows average differences with regard to three indicators for market structure. Sub-sectors K745 and K746 have above average entry-exit rates (relatively strong dynamic selection), while K742/3 (engineering and architectural services) and K744 (marketing services) have low entry-exit rates (i.e. sluggish selection dynamics).

Table A2 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)	Employment covered annually (x1000)	Productiv. level (x 1000 euro) [b)]	Average firm size (in empl. persons)	Average fixed capital per employed person [c)]	Average entry-exit rate [d)]
K720	245	335	1952	49.3	5.8	35.5	4.7%
K741	309	937	3363	38.9	3.6	32.3	4.2%
K742_3	365	591	1975	35.8	3.3	29.0	2.5%
K744	270	123	610	34.2	5.0	26.6	2.3%
K745	293	30	2014	25.5	66.2	5.7	7.8%
K746	278	21	594	19.0	28.2	11.1	5.1%
K747	305	101	2183	14.6	21.6	7.6	3.0%
K748	297	403	1504	29.6	3.7	34.8	4.7%
Total	2362	2542	14194				
Average				30.9	17.2	22.820	4.3%

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.
Data sources: own calculations based on Eurostat NewCronos data, SBS and EUKLEMS data.

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[34] In the main text additional data have been used for 1999, so that the total number of observations is about 2700.

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