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September 2012

Online at https://mpra.ub.uni-muenchen.de/41016/ MPRA Paper No. 41016, posted 03 Sep 2012 15:12 UTC

# Dynamic market selection in EU business services

## Henk Kox<sup>#)</sup> and George van Leeuwen<sup>&)</sup>

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#### Abstract:

European business services has witnessed about two decades of virtual productivity stagnation. The paper investigates whether this is caused by weak dynamic market selection. The time pattern 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. Between 1999 and 2005 we observe a persistence of scale inefficiencies and X-inefficiencies, with scale efficiency falling rather than growing over time. This indicates malfunctioning competitive selection.

The time pattern of inefficiencies is significantly explained by regulatory policies that hamper entry and exit dynamics and labour adjustment, and by a lack of import penetration. The results suggest that policy reform and more market openness will have positive productivity effects. This holds for business services itself, but also wider, because of business services' products are widely used as intermediary inputs in other parts of the European economy.

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

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

#### Acknowledgements

We thank George Gelauff, Isabel Grilo, Jarig van Sinderen, Coen Teulings and Paul Veenendaal for useful comments on earlier versions of this paper. We have also benefited from comments by participants at seminars at the European Commission (DG/IM, Brussels), La Sapienza University (Rome), CEPS (Brussels), NMA Dutch Competition Authority (The Hague), CPB (The Hague) and CAED (Nuremberg). Remaining flaws are ours.

An earlier version of this CPB Discussion Paper formed the basis for a paper in *Structural Change and Economic Dynamics* (Kox and van Leeuwen, 2012, <a href="http://www.sciencedirect.com/science/article/pii/S0954349X12000112">http://www.sciencedirect.com/science/article/pii/S0954349X12000112</a>).

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## 1. Introduction

This paper explores a new methodology for evaluating the effectiveness of dynamic selection in markets where scale economies are important. A key element for this analysis is the time pattern of scale-related inefficiencies in a market. 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). 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). 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.<sup>3</sup>

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 multicausality means that we cannot take the productivity distribution itself as an indicator of market efficiency.

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<sup>&</sup>lt;sup>1</sup> 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.

<sup>&</sup>lt;sup>2</sup> 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.

<sup>&</sup>lt;sup>3</sup> 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).

In this paper we have looked for firm characteristics that can be 'objectified' and still tell us something 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.<sup>4</sup> 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.<sup>5</sup> This industry had a zero or negative contribution to aggregate productivity growth in most of Europe.<sup>6</sup> The business services industry is the industry with the single largest contribution to Europe's productivity gap with the USA.<sup>7</sup> There may be further knock-on effects. Business services typically provide 15-20 per cent of all intermediary inputs.<sup>8</sup> 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. Size-dependent policies may create specific growth obstacles for firms in certain size classes and thus distort the firm distribution. Some authors have shown analytically that such policies potentially have a large impact on aggregate productivity both at the industry level and at the country level (Restuccia et al., 2008; Guner et al., 2008). Others like Garricano et al. (2012) and Bartelsman et al. (2012) have recently found empirical evidence for the productivity-distorting effects of size dependent policies. 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). 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. 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.

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<sup>&</sup>lt;sup>4</sup> Average for 2008 of all EU-15 countries except Greece and Portugal (OECD, 2011).

<sup>&</sup>lt;sup>5</sup> 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.

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.

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

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.

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 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 skillbiased 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 effectiveness 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<sup>9</sup> has a huge scale disadvantage relative to the most 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 framework for analysing dynamic competitive selection in markets

A weak productivity performance by firms may have several causes, varying from reasons that are typical for a particular firm to factors that are embedded in the structure of markets. Management may simply make wrong choices: buying bad inputs, employing the wrong workers, making products that they had better left to others, miscalculating consumer demand. These things happen all the time, but management errors can hardly explain why a complete industry like business services with more than 15 million workers in the EU experiences productivity stagnation during two decades. In competitive markets we would expect that efficient or innovative firms regard the erroneous decisions or inertness of other firms as a business opportunity. This market mechanism works in a market with homogeneous products, but also in a market with differentiated products.

Suppose business services markets would have perfect competition and homogeneous products. In that case there would be strong competitive interaction among firms. Firms with weak productivity (high

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 $<sup>^{9}</sup>$  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.

costs) would be punished by a lower market share and/or low profits. Conversely, efficient firms would have higher profits and/or a faster growth in market share. Such a process of selection by the market would ensure that firms cannot be careless about their efficiency and productivity. Moreover, firms must not only care about their current competitors, but also about potential competitors that –triggered by any rents or profits— may enter the market from outside as domestic start-ups or as foreign entrants (Baumol et al., 1982). As a consequence, firms must learn to improve their efficiency over time as a precondition for survival. The selection process and consequent market reallocation will cause average productivity to go up. Several models (Jovanovic, 1982; Hopenhayn, 1992; Melitz, 2003) consider markets with heterogeneous-productivity producers and derive a positive link between the producer's productivity level and survival in the industry. Aggregate productivity in the industry goes up due to two effects: the reallocation of market shares to the more efficient producers, and by the market incentive to adopt better technologies and production methods.

The competitive selection mechanism also works in markets where monopolistic competition and product differentiation prevail (Dixit and Stiglitz, 1977; Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009; Asplund and Nocke, 2006). If the consumers have a sufficient taste for variety, firms may be monopolists in their own-created market niches. In the short term this might make firms a bit more careless about efficiency and competition, but not in the longer term. 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 costs. They incur losses, lose market share, and eventually drop out. If fixed start-up costs are important in this industry, this will even strengthen the competitive pressure. Again here, free entry and contestable markets serve to drive up efficiency by creating an incentive to adopt superior technologies., and by reallocation of market shares to more efficient producers.

Both types of textbook models could generate a weaker productivity-based reallocation process if (a) free entry becomes subject to obstacles; (b) a substantial part of firms experiences post-entry growth obstacles; (c) large incumbents are shielded-off from efficiency-based competition; (d) exit costs slow the shrinking of inefficient firms. Furthermore, shallow regional markets with few competitors and weak competitive interaction would also diminish the effectiveness of productivity-based market selection. A long-term productivity stagnation like has been found in European business services is neither compatible with the competitive homogeneous-product market nor with the competitive differentiated-product market. So it is plausible to investigate whether something could be wrong the preconditions for competitive interaction.

## Limitations of existing competition indicators

Competition is a multi-facetted phenomenon that is easily spoken off, but not easy to measure empirically. A problem is that most definitions of competition and markets are self-referring. This is also the case with

the juridical concept of the relevant market that is central in most competition policies. "The main goal of market definition is to assess the existence, creation or strengthening of market power, which is defined as the ability of the firm to keep the price above the long-run competitive level" (OECD Competition Committee 2012). The relevant market should be defined in a way such that the competitive constraints a firm faces, i.e. demand and supply side substitution, are captured as accurately as possible. The one way to define a relevant market is by assessing the scope (products and regions) in which a hypothetical profitmaximising monopolist could inflict a Small but Significant Non-transitory Increase in Price or shortly, SSNIP (e.g. Ivaldi and Verboven, 2005). This may work for competition policies that target at dominant market position of individual large suppliers, but this individual-firm-based approach is empirically useless for assessing the performance of a market as a set of firms. Because of their differences in regions and products, one would have to do this test for every individual firm. Hence, the test is difficult to apply in two-sided markets, which involve platforms serving distinct groups of consumers in the presence of indirect network effects. The 'classic' market identification approach defines a relevant market by assessing where the cross price elasticities with other product or regional markets are zero. Empirically this method is also difficult to apply. 10 Many markets are in constant state of turbulence, with marketshare reallocation, entry and exit, introduction new products, disappearance of other products, foreign direct investment, outsourcing and imports and exports. So, market boundaries are seldom stable over time. In industries exhibiting rapid innovation, the boundaries of any defined market may change rapidly over time. Competitive interaction includes many dimensions of individual firm behaviour that mostly cannot (or only partly) be observed. Causality questions abound if we would try to evaluate the links between the complex interplay of independent actions, reactions, anticipations, and inertness of market players. External shocks (macroeconomics, regulation, globalisation, technology) change market interaction all the time.

The OECD Competition Committee in June 2012 concluded that "an increasing number of OECD jurisdictions are reconsidering the role of market definition and are embracing new approaches to overcome its limitations in particular cases. Some jurisdictions have emphasised that market definition is not an end in itself, does not need to be a first step in any competition analysis nor has to be employed in all cases. Rather than abandoning market definition, most jurisdictions complement it with additional approaches". So, the floor is open for new analytical instruments, and this paper offers one.

## Intuition behind our framework of analysis

Given the limitations of the standard quantitative indicators for competition intensity and dynamic market selection we propose an alternative analytical framework. The framework is closely related to standard microeconomic theory of dynamic selection processes in markets for homogeneous and differentiated products. It evaluates changes in the characteristics of firm distributions between  $t_0$  and  $t_1$ . The most

<sup>&</sup>lt;sup>10</sup> In an integrated market area, this is condition is seldom fulfilled, so that one then has to introduce arbitrary threshold values for the cross price elasticities.

simple and straightforward approach to assess the role of productivity-based market reallocation is to take an efficiency measure like labour productivity and assess whether the more productive firms have increased their share in the industry between  $t_o$  and  $t_l$ . However, doing so assumes that all firms can be directly compared. But could we reasonably compare a small Italian software developer with five employees with a European software giant like SAP? It is very unlikely that both have access to the same production method (technology, internal specialisation). Part of the productivity difference between these two companies is then related to firm size rather than being caused by the competitive interaction. These size-related issues tend to impact the firm's efficiency performance, and must be taken into account when measuring the effectiveness of dynamic market selection. Small firms may be flexible, but they have less scope for internal division of labour than large firms. Small-firm employees are typically more involved in multi-tasking, which comes with a productivity disadvantages (cf. Coviello et al., 2010). Conversely, large firms may be good in splitting tasks and applying internal division of labour, but they are less flexible, often find it more difficult to monitor and motivate their personnel, and have an imminent tendency towards bureaucracy. If a particular size class in an industry combines the best of large-firm and small-firm characteristics and thus gets the highest output from a given combination of inputs, we call it the optimal firm size.

In an efficient market with profit-maximising firms all firm would try to operate close to optimal scale size, because this is the size at which total profits are at their maximum. Small firms 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. Over time, after a process of adapting, growing and shrinking, only firms of optimal size would be left in the steady-state size distribution (De Wit 2005). We take this steady-state firm distribution as a starting point for our framework of analysis for industries that are subject to significant scale economies.

Our indicator of efficient market selection measures two elements: (1) the extent to which the most efficient firms per size diminish their efficiency gap with the optimal size class, and (2) the extent to which the forms within size classes diminish their efficiency gap with the frontier firms in their own size class. We start with a snapshot at a given point in time, depicted by Figure 1. It compares an industry where fixed costs and scale economies matter with a fully competitive market where all firms have attained optimal size Q at steady state. The efficiency of the optimal-sized firms Q is represented by the dashed line; it is our counterfactual benchmark. Without loss of generality this value may be set to 1 (one). The dimension of the efficiency index can be chosen at will: labour productivity (physical or in value terms), average costs per unit, or more complex efficiency indices derived from data-envelopment

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<sup>&</sup>lt;sup>11</sup> Young entrants may set their prices even lower than incumbents (cf. Foster et al., 2008), increasing the potential threat to inefficient incumbents, but also increasing the risk for themselves of an early exit, because it adds to their scale disadvantage.

analysis. Using total factor productivity (either in physical or in value terms) is less adequate because of the underlying assumptions used for its calculation.<sup>12</sup>

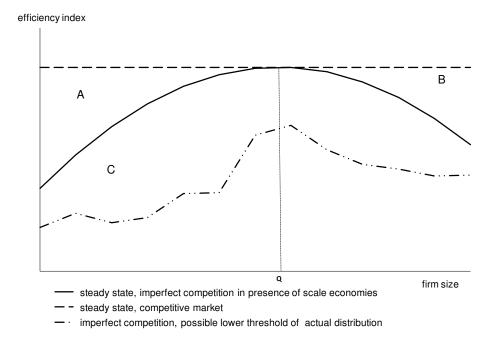


Figure 1 Framework for analysing firm size, productivity and market selection

Now consider a market with imperfect competition where not all firms have achieved optimal firm size Q. In this situation one finds firms of all size classes, larger and smaller than Q. A size classes is an interval within which firms are heterogeneous with respect to efficiency. We first focus on the best-performing (frontier) firms with each size class. Even these firms typically have a lower efficiency than the frontier firms in the optimal size class, as is indicated by the parabolic solid line in Figure 1. Only the optimal-sized frontier firms achieve efficiency level 1; the frontier firms of other size classes operate somewhere between efficiency levels 0 and 1.

So far we only dealt with the best-performing firms in each size class, those that operate *on* the solid line. The efficiency of the *worst*-performing firms by size class is depicted by the dot-dashed line. The area circumscribed by the solid and the dot-dashed line holds all other firms of a size class. Figure 1 allows distinguishing three types of failure in competitive market selection:

The choice of the efficiency index requires separate attention because it may affect the outcomes. Foster et al. (2008) have shown that price-based and quantity-based TFP measures may lead to different conclusions because the underlying behavioural assumptions may diverge from actual firm behaviour in markets. For TFP to be a correct measure of multi-factor productivity a number of crucial preconditions for the operation of input and output markets must be met. Because market conditions in the output market are precisely what we intend to investigate, we think that using TFP efficiency measures are out of the question.

Empirically this may be done by taking the average performance of the x% (say 3 or 5%) most-efficient firms within each size class. This approach reduces the risk of a bias due to atypical outliers.

- Region A reflects market obstacles that impede firms to grow towards size *Q* like commercial setup costs, or regulatory entry barriers. There may also be post-entry growth barriers like administrative burdens, tax obligations or labour laws that contain size-specific hurdles.<sup>14</sup>
- Region **B** reflects obstacles that make shrinking to size *Q* less attractive. Such exit or shrinking barriers may stem from labour laws, bankruptcy laws, or the tax system. The market power of these large firms could also lower the need for them to operate at the optimal size.
- Area C covers all remaining sub-frontier firms that survive in shallow or non-transparent markets
  with weak competitive interaction (countryside areas, no import competition, product niche
  markets). Product-market regulation that protects inefficient incumbent firms against new entrants
  may be another reason.

Region **A** and **B** are size-related inefficiencies; they will jointly be labelled as *scale-inefficiency*. The inefficiencies depicted by area **C** are not size-specific; we use the term *X-inefficiency* for this area. Figure 1 pictures (in)efficiency scores at one moment in time. Both indicators identify to what extent firms make the most of a given set of resources. This information is meaningful, but still says nothing about the dynamics of competitive market selection. For that reason, the same analysis must be repeated at a different moment in time. This gives us a "warning device" for identifying malfunctioning markets. In a market with strong dynamic selection we expect a an increase in scale efficiency and/or X-efficiency. In uncompetitive markets both values will be zero or positive: inefficiencies persist or increase. <sup>15</sup>

## How does this approach compare to other competition indicators?

Most quantitative stand measures focus on particular market *outcomes* like market shares or the structure of rents. The Hirschmann-Herfindahl index and the *Cx* concentration indices (with *x* representing the the cumulative market share held by the *x* largest companies) measure the structure of market shares. The problem with these indicators is their interpretation of market reallocation. An increase of market concentration may either reflect weakened competition (market power, collusion) or it may reflect more intense competition that causes a shift of market shares towards the most efficient firms (Boone et al. 2007; Boone 2008). A similar problem occurs with the Lerner index (price-cost margin) that is supposed to measure competition intensity by the reduction of rents or profit margins. An increase of the price-cost margin cannot be interpreted unequivocally. It can either mean a weakened competition (market power, collusion) or indicate that intensified competition has resulted in market-share reallocation towards the most efficient firms that have higher profits per unit. Another outcome-oriented competition measure is Boone's profits elasticity indicator (Boone, 2004; 2008). It is defined as "the percentage fall in profits due to a percentage increase in marginal costs". 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

allows to express them in logarithms.

By a [x+1]/2 scalar the first derivatives of scale efficiency and X-efficiency can also be transposed in the [0,1] space, which

 $<sup>^{14}</sup>$  Cf. Garicano et al. (2012), Bartelsman et al. (2012), Restuccia and Rogerson (2008) and Guner et al. (2008).

profits elasticity indicator measures how elastic a firm profits are with respect to differences in marginal costs. This indicator is superior to the price-cost margin, because it yields a more appropriate interpretation of dynamic market reallocation to more efficient firms. Because of its sole focus on marginal costs the profits-elasticity measure can correctly interpret competition intensity in markets where constant returns-to-scale dominate. However, its competition assessment may become biased in markets where fixed costs and increasing returns to scale play a role. More entry of small firms may increase profit elasticity among small firms, but that is not a sufficient condition to conclude that competition intensity in the market has increased (e.g. von Weizsäcker 1980; Lahiri and Ono 1988; Boone 2001). Suppose that the application of the most efficient technologies is conditional upon certain fixed-cost outlays, and that credit constraints form an obstacle for small firms to afford such fixed-cost outlays. Then *de facto* the level of marginal costs has become positively related to the level of fixed costs per unit. For the market as a whole, an increase in profit elasticity only represents a welfare improvement if it results from a market reallocation towards the efficient (and in this case) larger firms. Our indicator has the potential to be a better empirical proxy of competitive selection in industries where scale economies are strong. This is relevant since the literature indicates that scale economies are important in IT, software and business services.

## 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. <sup>18</sup> 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.

<sup>16</sup> Small firms typically have higher fixed costs per unit than larger firms. This also holds for European business services as Figure A2 in the annex shows.

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<sup>&</sup>lt;sup>17</sup> Klette (1999) found that there is more variation in market power and scale economies within an industry than between industries. Markusen (1989), Francois (1990) and Marrewijk et al. (1997) point out that most producer services are characterized by important scale economies. Shy (2001) deals with scale economies in IT industries.

<sup>&</sup>lt;sup>18</sup> See Cantner *et al.* (2007), Coelli *et al.* (2005) and Banker *et al.* (2004).

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<sup>19</sup>

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  $\lambda_i$  (i=1,...,n) are nonnegative scalars such that  $\sum_{i=1}^{n} \lambda_i > 0$ . Each  $\lambda_i$  ( $k \in i$ ) 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 exist. The input-oriented efficiency parameter  $\prod_{zv}$  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  $\prod_{zv} = 1$ , and for the non-frontier  $\prod_{zv} \le 1$ . 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  $\lambda_i$  and frontier efficiency  $\prod_{zv}^{v_{crits}}$  by solving the linear programming system:

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

$$(3.1)$$

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:

<sup>19</sup> For expositional simplicity we briefly describe the general method. In the actual calculations we use a two-input (capital, labour) and one-output model. For multiple output/input cases, see Zhu (2009).

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.

$$Eff_{i} = i \mid \Pi_{i}^{crts} = 1, i = 1, ..., n = i \mid h_{i}^{rel} = 1, i = 1, ..., n$$

$$Ineff_{i} = i \mid \Pi_{i}^{crts} < 1, i = 1, ..., n = i \mid h_{i}^{rel} < 1, i = 1, ..., n$$
(3.2)

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

$$DTF_{i} = 1 - \prod_{i}^{crts} = 1 - h_{i}^{rel} \quad ; \quad 0 (frontier) \le DTF_{i} < 1$$

$$(3.3)$$

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 3 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 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  $z^*$ ,  $z_w$  and  $z_C$ . 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 shortterm 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

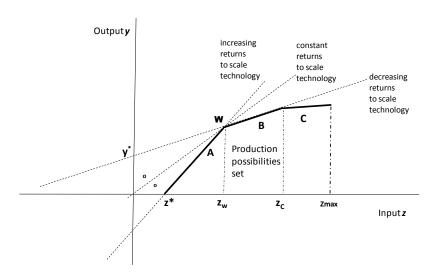


Figure 3 Production possibilities and input-measured firm size

dmu v under a constant-returns-to-scale (CRTS) assumption. The more stringent sum condition  $\sum_{i=1}^{n} \lambda_i = 1 \text{ will force dmu } v \text{ to be only compared with similar-sized other dmu. That allows to calculate variable-returns-to-scale (VRTS) efficiency parameters (e.g. Cantner et al. 2007). We thus set up a VRTS version of the linear programming problem to obtain a new set of <math>\lambda$  weights and a set of  $\Pi_{zv}^{*vrts}$  efficiency parameters that *only* reflect X-efficiency, free of scale effects:

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

$$(3.4)$$

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:

$$Eff_{i}^{vrts} = i \mid \Pi_{i}^{vrts} = 1, i = 1, ..., n = i \mid h_{i}^{rel, vrts} = 1, i = 1, ..., n$$

$$Ineff_{i}^{vrts} = i \mid \Pi_{i}^{vrts} < 1, i = 1, ..., n = i \mid h_{i}^{rel, vrts} < 1, i = 1, ..., n$$

$$(3.5)$$

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:<sup>21</sup>

$$\Pi_{i}^{crts} = SCE_{i} . \Pi_{i}^{vrts} \iff SCE_{i} = \frac{\Pi_{i}^{crts}}{\Pi_{i}^{vrts}} ; 0 < SCE_{i} \le 1 (frontier)$$
(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  $SCE_i = I$ , 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  $SCE_i = I$  holds. Empirically, the most-efficient scale size is the one for which average  $SCE_s$  is closest to one:<sup>22</sup>

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

<sup>&</sup>lt;sup>21</sup> 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.

The distribution of size classes ranked by relative scale efficiency may have more than one local maximum.

measurement error considerably.<sup>23</sup> 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 used a parametric stochastic frontier (SF) model as a robustness check; the results confirm that non-constant returns to scale dominate in the European business-services industry.<sup>24</sup>

#### 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 specific information about a country × industry × size class combination: the number of firms, total sales, total value added, number of employed persons, and depreciation. It allows to construct a representative firm (dmu) by data cell that also says something about the intra-cell distribution. Recent findings on firm size distributions suggest a fractal (self-replicative) size distribution across and within size classes (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 database 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.<sup>25</sup> 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).<sup>26</sup> 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. The data annex (tables A2 and A3) provides further information on data heterogeneity by industry, country and size class.

The DEA efficiency indices reflect both labour productivity (value added per full-time worker in constant prices) and capital efficiency (units of value added per unit of depreciation, both in constant

 $<sup>^{23}</sup>$  The potential effects of outliers and statistical noise is discussed at greater length in the data annex of this paper.

<sup>&</sup>lt;sup>24</sup> Reported in Kox, Van Leeuwen, Van der Wiel (2010).

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.

<sup>&</sup>lt;sup>26</sup> Between 2000 and 2005, the data cover 2.5 million EU business services firms and 14.1 million employees.

prices). While our data would have allowed using total factor productivity (TFP) instead, we have deliberately chosen not to use this measure. TFP is by definition 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 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 ( $\Pi_{is}^{*crts}$ , CRTS), X-efficiency ( $\Pi_{is}^{*vrts}$ ), 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.

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).

Table 1 Efficiency scores by size class, across sectors, countries and years (1999-2005), medians by size class<sup>a)</sup>

Size classes	CRTS efficiency <sup>b)</sup> Π *crts / is	Scale efficiency (SCE <sub>i</sub> )	X-efficiency (VRTS) $\prod_{is}^{*vrts}$
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

<sup>&</sup>lt;sup>a)</sup> The average number of scale indices per size class is 591, of which the median value is presented. <sup>b)</sup> Calculated as median DEA CRTS efficiency (=scale efficiency times X-efficiency). Source: own calculations.

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.

The vast majority of the observations are found to operate in the increasing-returns-to-scale region of the production function, while also a considerable subset of observations (mainly in large size classes) operates in the decreasing-returns-to-scale region.<sup>27</sup> The distribution of the marginal DEA-scale efficiencies therefore permits the conclusion that many small firms have the potential to increase their productivity by a better use of scale economies. Size class 4 with 50-249 employees can be considered as the optimal size class, but 97% of the potential scale efficiency gains are already exhausted by reaching size class 2 after passing the 20 employees threshold. Our scale-efficiency results 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 about one-third of total employment in European business services (cf. Table A1).

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 4 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

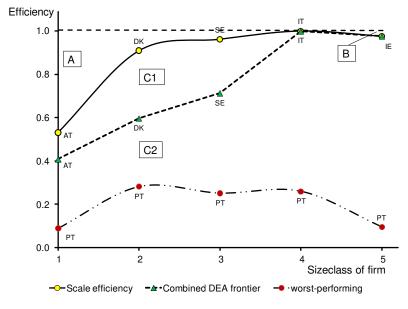


Figure 4 Scale performance in Architectural, Engineering & Technical Services (K742-3), per size class, 2005

Note: AT =Austria; DK=Denmark; SE=Sweden; IT=Italy; IE=Ireland; PT=Portugal. We have suppressed the data points for other countries, to avoid that the graph becomes too cluttered.

Figure 1, but now with real data. 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-

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<sup>&</sup>lt;sup>27</sup> This test is reported in Kox, Van Leeuwen, Van der Wiel (2010).

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. 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. 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

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

Industry	Change in X-efficiency (no. of observations) <sup>a)</sup>			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	

<sup>&</sup>lt;sup>a)</sup> 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.

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 3 repeats this analysis at the country level. X-efficiency has has 'net' 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.

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

Industry	Change in X-efficiency (no. of observations) <sup>a)</sup>			Change in scale efficiency (no. of observations) <sup>a)</sup>			
	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	

<sup>&</sup>lt;sup>a)</sup> 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.

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

Size class	Change (no. of	Change in X-efficiency (no. of observations) a) diminish zero increase			Change in scale efficiency (no. of observations) a)			
	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		

<sup>&</sup>lt;sup>a)</sup> 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 diminished only in Austria, Belgium, Spain, France, Sweden and UK.

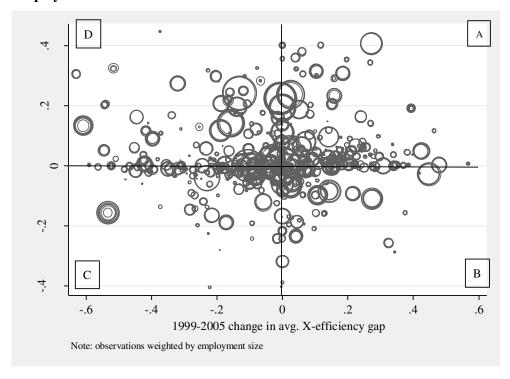
Table 5 Change in average efficiency gaps, by country over time interval 1999-2005

Country		e X-efficiency gap ervations) <sup>a)</sup>	Change in average scale-efficiency g (no. of observations) <sup>a)</sup>		
	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	

<sup>&</sup>lt;sup>a)</sup> 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 5 is a scatter plot of the employment-weighted change in the average size of efficiency gaps within and between size classes. The

Figure 5 Change in average efficiency gaps over 1999-2005 interval, observations weighted by employment size



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 5. 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.

**Robustness check**. Our frontier calculations are based on a uniform efficiency benchmark for each industry and year, the optimally efficient size class. On that basis we have calculated scale efficiency. Our basic analytic framework developed in Section 2 assumes that in a competitive market firms of all size classes compete with each other, so that their efficiencies converge over time. When an industry shows no or weak scale-efficiency convergence this indicates weak competitive market interaction. For the smallest size class this resulted in the puzzlingly low scale efficiency of 0.49 reported in Table 1. Moreover, Tables 4 and 5 even reported a further worsening of scale efficiency during the period 1999-2005. This raises the question whether perhaps our model assumption as to the scale efficiency is wrong:

Could it be the case that small firms systematically operate, interact and compete in their own size-related sub-market and not with other size classes?

As a robustness test we have investigated this alternative assumption, according to which the relevant market would only be formed by firms in the same size class. If this is true we would expect that the efficiency of firms converges towards the efficiency frontier *of their own size class*. Hence, we should find a right-skewed distribution of efficiencies, leaning towards the size-class' own efficiency benchmark. This should also hold for the smallest firms if they indeed interact competitively in their own size class.

Figure 6 plots the efficiency distribution of firms relative to the best-performing firms in their own size class on a {0,...,1} scale for the year 2005. All size classes - except the smallest - have a right-skewed efficiency distribution, whereas the size class 1 has a relatively heavy mass of inefficient firms. This result offers no support whatsoever for the alternative hypothesis that the smallest firms would have a strong mutual competition, since this does not even show up in their own size class. Also the dynamic analysis offers insufficient evidence for the hypothesis that markets would coincide with size classes. We therefore see no reason to drop our basic analytic framework. The efficiency distribution found in the top left panel of Figure 6 seems to fit a market situation where from an efficiency perspective 'anything goes', because firms have weak interaction.<sup>29</sup>

<sup>&</sup>lt;sup>28</sup> However, in dynamic terms the median efficiency in the smallest size class between 1999 and 2005 witnessed some convergence to the size-class benchmark, especially in 'architects and engineering' and in 'marketing & advertising'. In other

industries, we found no such efficiency convergence for the smallest size class. In 'accountancy, legal & consultancy services' and in 'labour recruitment' we even found a relatively deteriorating performance of the smallest size class in this robustness test.

Possible explanations are that small firms operate more often in local and shielded niche markets, where personal relations with clients dominate, where prices or product quality are low, and/or where residual incomes may be lower than elsewhere in the market. Further research is necessary to investigate this.

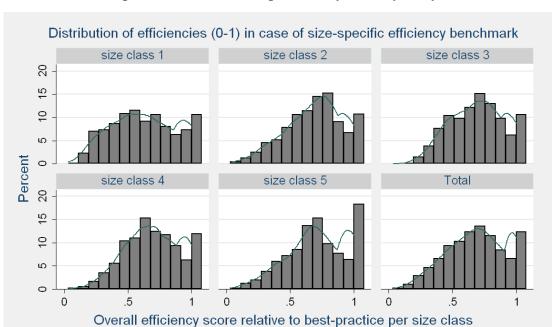


Figure 6 Robustness test: distribution and kernel density of relative efficiency compared to size-class best practice (by industry and year), data 2005

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 on weak market interaction and poor competitive selection may offer an explanation for the negative TFP-growth in EU business services as has been found in several growth-accounting studies.

## 4. Explaining scale-related inefficiencies

This section sets out to identify the market and environment factors that explain the different country and industry patterns in scale- and X-inefficiencies. We test the hypothesis that regulatory characteristics and market contestability variables have a significant impact competitive interaction and the degree of efficiency convergence in a market. 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  $\Pi_{sjkt}^{*VRTS}$ :

$$SCE_{kjst} = \psi \mathbf{M}_{kjst} + \varphi \mathbf{R}_{kjst} + \alpha_1 \mathbf{z}_s + \alpha_2 \mathbf{z}_j + \alpha_3 \mathbf{z}_t + \upsilon_{kjst}$$

$$\Pi_{kjst}^{*VRTS} = \beta \mathbf{M}_{kjst} + \lambda \mathbf{R}_{kjst} + \delta_1 \mathbf{z}_s + \delta_2 \mathbf{z}_j + \delta_3 \mathbf{z}_t + \mu_{kjst}$$

$$(4.1)$$

The suffices refer to country (k), industry (j), size class (s) and year (t). All continuous variables are expressed in natural logs.

<sup>&</sup>lt;sup>30</sup> 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.

in which  $\mathbf{z}_j$  and  $\mathbf{z}_s$  are vectors of fixed-effect dummy variables for, respectively, industries, size classes and year; the  $\mathbf{M}$  vector collects explanatory variables for market contestability, the  $\mathbf{R}$  vector contains variables for the regulatory environment, while  $\upsilon_{sjkt}$  and  $\mu_{sjkt}$  represent error terms. We start with a simple model with one  $\mathbf{M}$ -variable and one  $\mathbf{R}$ -variable, subsequently we use an array of variables for each.

Because the persistence of scale-specific diseconomies is the dependent variable here, we cannot use any market structure variables that reflect *outcomes* of competitive selection. This holds e.g. for like market concentration ratios. So, for the **M** vector we focus on factors that proxy the (exogenous) contestability of the incumbents' market. The first indicator is import penetration, measured as the share of imports in total domestic use of business services.<sup>32</sup> The second indicator is the start-up rate of new firms.<sup>33</sup> 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 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 to what extent it promotes scale efficiency depends on the size structure of the national market that they are entering. 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 data problem is that the number of observation drops by almost one-quarter if we include the domestic start-up ratio, due to missing data. We therefore start with only import penetration in the **M** vector. This variable ranges between 0.06 (France) and 0.6 (Ireland) in 2005.

For the **R** vector with indicators for the regulatory environment we first use an umbrella indicator regulation-caused costs of doing business (labelled Raba), derived from the World Bank Cost of Doing Business database. This indicator 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 –

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<sup>&</sup>lt;sup>32</sup> 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.

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, even though this method is like to understate the real annual start-up rate, because of non-observed exits, as the net growth rate of the number of firms per data cell  $\Delta nof_{kist} / nof_{kist-1}$ .

and paying taxes. The indicator varies by country and year is constructed from the data at the highest level of detail.<sup>34</sup> A higher value of *Raba* always reflects more business costs. The second model replaces *Raba* by a set of three specific indicators for regulatory entry costs, exit costs and labour-adjustment costs of firms:<sup>35</sup>

- for regulatory exit costs we use *costs of closing a business* (labelled *Rclo*) taken from the same World Bank source.
- for regulatory entry costs of new firms we use the OECD indicator *market access barriers in professional services* (labelled *Rmaps*). It measures by country and year the incidence entry barriers: barriers to becoming a member of each of the professions, licensing and educational requirements, quantitative constraints on the number of suppliers of professional services and/or exclusive rights granted to suppliers in certain areas. Because the incidence of market access barriers wil vary with
- For the regulatory costs of employment adjustment in case of growth or shrinking of a firm we use the OECD *labour protection indicator* (labelled *Remplad*), measuring the costs involved in dismissing individuals or groups of workers and the procedures involved in hiring workers on fixed-term or temporary work agency contracts.

All regulation indicators have been expressed as index numbers relative to the annual average for the sample countries. They all increase in the intensity of regulatory barriers. Multicollinearity between the three indicators is in the acceptable range of 0.1 to 0.2. The full data set with data for 13 countries, eight industries, and five size classes and seven years (1999-2005) has a panel structure, holding information on both the intertemporal dynamics and on the observed group entities. The panel structure allows dealing efficiently with unobserved or missing variables. A Tobit regression is applied to estimate model (4.1). The random-effects Tobit panel estimator can handle the continuous but censored nature of the DEA variables (cf. Hsiao 2006). The random-effects (RE) variant accounts for the possibility that our selection of countries and industries has an impact on the results. An additional reason to apply RE relates to our data structure. 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. This limitation rules out the use of a model with firm-level fixed-effects, but a RE model is a good stand-in.

Table 6 reports the marginal effects of a change in the explanatory variables on the conditional mean of, respectively, DEA X-efficiencies and DEA scale efficiencies. Because all continuous variables are expressed in logarithms, the estimated parameters may be read as elasticities, giving the x% change in the conditional mean of the DEA scale- or X-efficiencies after 1% change in an explanatory variable.

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<sup>&</sup>lt;sup>34</sup> 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.

<sup>&</sup>lt;sup>35</sup> Further details on the used variables are provided in the data annex.

Table 6 Explaining scale efficiency and X-efficiency performance, using Tobit panel estimator with random effects

	Scale efficience	ey: $\log(SCE_{kjst})$	X-efficiency: le	$\log(\prod_{kjst}^{*VRTS})$
	Model 1	Model 2	Model 1	Model 2
Regulatory environment:		<pre><preferred></preferred></pre>		<pre><preferred></preferred></pre>
* Umbrella indicator Raba (log)	- 0.025 (0.030)		- 0.116 *** (0.050)	
* Market access, Rmaps (log)		- 0.152 *** (0.027)		-0.010 (0.031)
* Labour protection, Remplad (log)		- 0.027 (0.031)		-0.155 *** (0.037)
* Closing a business, Rclo (log)		-0.018 (0.038)		-0.221 *** (0.053)
Market contestability:				
* Import penetration (log)	-0.008 (0.020)	0.010 (0.022)	0.061** (0.027)	0.075 *** (0.029)
* Start-up ratio (log)		0.005 (0.004)		- 0.007 (0.007)
Fixed effect size-class <sup>a)</sup>	Yes	Yes	Yes	Yes
Fixed effects by 2-digit industry b)	Yes	Yes	Yes	Yes
Fixed effect Ireland c)	Yes	Yes	Yes	Yes
No. of groups	499	491	499	491
Avg. no. of observations per group	5.4	4.6	5.4	4.6
Total no. of observations	2696	2270	2696	2270
RE variance (sigma_u)	0.33	0.32	0.32	0.31
Rho: share of RE in total variance	0.83	0.82	0.60	0.58
Wald chi2	50.1 ***	78.8 ***	52.1 ***	81.4 ***
Log likelihood fitted model	326.4	216.1	-1003.7	-875.2

<sup>&</sup>lt;sup>a)</sup> Benchmark is the smallest size class with 1-9 employed persons. <sup>b)</sup> Benchmark is the computer services industry (K720). <sup>c)</sup> Dummy for Ireland, because of its exceptionally high import penetration. \*\*\* indicates statistical significance at the 1% confidence level based on Z values. Source: own calculations.

In both models the regulatory variables always have the expected negative sign. However, for the explanation of scale efficiency, only the regulatory market access barriers have a statistically significant impact. A 1% increase in Rmaps goes along with a 0.15% fall in scale efficiency. In the case of within-size class efficiency (X-efficiency), all regulatory variables have a negative impact that is statistically significant at the highest confidence level. A 1% increase in Remplad and Rclo goes long with, respectively, a 0.16% and a 0.22% fall of X-efficiency. Conversely, import penetration has a significant positive impact on X-efficiency, showing that that the market contestation effect dominates here. The sign of the estimated import penetration coefficient could indicate that imports have a business-stealing effect on scale efficiency. Domestic start-up ratios in none of the regressions have a significant impact.

We do several robustness checks to investigate the stability and soundness of the Tobit results. The first column of Table 7 presents the results of an OLS regression with White-robust standard errors for the same sample. In the second column we do the same, but now with the smallest size class deleted from the sample in order to investigate whether perhaps the smallest size class drives our results. The third column runs an

OLS regression on the full sample, but now with standard errors clustered by country to investigate the role of unobserved country heterogeneity. Because the random-effects Tobit model is relatively sensitive to regression errors that are not normally distributed, we test the robustness by using a bootstrap procedure for deriving reliable standard errors. The last column presents the results of a Tobit RE regression where we bootstrap the standard errors by 50 replications for each group using random draws from the full variation range of the explanatory variables. We disregard the role of the start-up ratio, because of the zero results so far and because of the many missing observations for this variable.

Table 7 Robustness tests model 2 (without start-up ratios): alternative specifications and estimation procedures

	Dep. variable	log total efficiency	(= scale efficiency	* X-efficiency)
	(1) OLS	(2) OLS only size classes 2-5	(3) OLS with SE clustered by country e)	(4) Tobit RE with bootstrapped SE <sup>c)</sup>
Regulatory environment:				
* Market access, Rmaps (log)	-0.134 *** (0.016)	- 0.091 *** (0.018)	-0.134 ** (0.053)	-0.151 *** (0.031)
* Labour protection, Remplad (log)	- 0.277 *** (0.020)	- 0.223 *** (0.022)	- 0.277 * (0.138)	- 0.209 *** (0.034)
* Closing a business, Rclo (log)	-0.253 *** (0.029)	-0.218 *** (0.031)	-0.253 * (0.122)	-0.246 *** (0.051)
Market contestability:				
* Import penetration (log)	0.057*** (0.017)	0.072*** (0.017)	0.057 (0.108)	0.032 (0.034)
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	2140	2696	2696
R <sup>2</sup> adjusted	0.22	0.18	0.23	
RE variance (sigma_u)			0.297 ***	0.297 ***
F test	39.1 ***	25.1 ***		
Wald chi2			232.5 ***	548.6 ***
Akaike information criterion	2653	1697	2640	2081
Log likelihood fitted model	-1308	-829.3	-1308	-1020

<sup>&</sup>lt;sup>a)</sup> Benchmark is the smallest size class with 1-9 employed persons. <sup>b)</sup> Benchmark is the computer services industry (K720). <sup>c)</sup> 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. <sup>d)</sup> A dummy for Ireland is applied because of its exceptionally high import penetration.. <sup>e)</sup> Standard errors were adjusted for all 13 countries. Source: own calculations.

Table 7 shows that all main results of table 6 are reproduced in the tests, which shows the stability of our findings. The estimated parameter values in most cases increase, especially for the regulatory variables that all have a statistically significant and negative impact on total efficiency. Geographically clustering of the standard errors and the bootstrap test indicate that the import penetration no longer is statistically significant, and that apparently the regression errors for this variable are not normally distributed.

Possibly this change is due to the fact that a lack of detailed data forced us 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. The results reported in the second column allow us to rule out the possibility that our results are mainly driven by the performance of the smallest size class.

The results of the main tests and robustness checks in this section allow us to conclude that the pattern and persistence of scale inefficiency and X-inefficiency are negatively affected by regulation-caused costs of market access, labour adjustment and firm exit and by a lack of import competition.<sup>36</sup>

## 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.<sup>37</sup> 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.

We further investigated the factors that explain the variation between countries and industries in the persistence of scale-related inefficiencies. To find out we have done 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-size class competitive selection, but was found not to have a significant impact on scale efficiency. Robustness tests have 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

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<sup>&</sup>lt;sup>36</sup> We did further regression analysis at the level of individual industries and size class. The detailed results are available from the authors upon request.

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.

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.<sup>38</sup>

## 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 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  $\lambda_i$  is smaller than some arbitrary size limit  $\Lambda$  equals:

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

with  $\lambda_o$  being the minimum firm size and  $\alpha$  the shape parameter of the distribution. For firms the minimum size is one employed person. Axtell found that for US business the shape parameter ( $\alpha$ ) 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  $\alpha$  in our case is even closer to unity: 1.055 which implies that the size distribution is "Zipfian".

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

<sup>38</sup> 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.

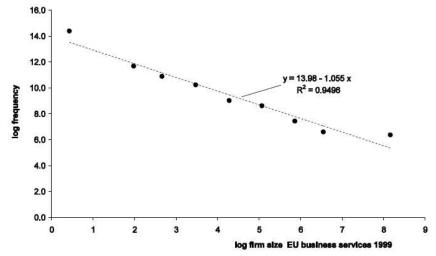
The Gini coefficient with support [0,1] is calculated as [  $2\alpha$  - 1]-1 and amounts to 0.9009, which confirms the very skewed character of the distribution.

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:

$$\Pr\left[MIN_{j} \le \lambda_{i,j} < MAX_{j}\right] = \int_{MIN_{j}}^{MAX_{j}} f(\lambda_{i,j}) d\lambda_{i,j} = \left(\frac{MIN_{j}}{\lambda_{i,j}}\right)^{\alpha}$$
(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.

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



**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.

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:

$$\hat{Y} = Y + w_y$$

$$\hat{X} = X + w_x$$
(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 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 inputoutput 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 and the OECD. We use four regulatory indicators:
- (a) an overall World Bank index based on 28 sub-indices for policy-caused business costs The data capture both the relative strictness of the regulations themselves as well as the efficiency of the national regulatory apparatus that implements the data. <sup>40</sup> For the sample countries it varies between 0.21 and 0.8
- (b) for regulatory exit costs we use costs of closing a business (labelled Rclo), derived from the same World Bank source. 41 For the sample countries it varies between 0.3 and 0.8.
- (c) for regulatory entry costs of new firms we use market access barriers in professional services (labelled Rmaps) produced by the OECD Economics Department (Conway and Nicoletti, 2008). This indicator measures by country and year the incidence entry barriers: barriers to becoming a member of each of the professions, licensing and educational requirements, quantitative constraints on the number of suppliers of professional services and/or exclusive rights granted to suppliers in certain areas. 42 For the sample countries it varies between 0.1 and 0.8. (d) For the regulatory costs of employment adjustment we use the OECD labour protection indicator (labelled Remplad). It measures the procedures and costs involved in dismissing individuals or groups of workers and the procedures involved in hiring workers on fixed-term or temporary work agency contracts (Venn, 2009). For the sample countries it varies between 0.26 and 0.8.
- D. Some descriptive statistics. Table A1 presents descriptive statistics on the country variation in the data set for the period 2000-2005, covering 2.8 million EU business services firms with 15.4 million employed persons. 43 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.

#### E. Role of scale economies in European business services

<sup>&</sup>lt;sup>40</sup> 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 subaggregates of business costs.

Documented in: <a href="http://www.doingbusiness.org/research/resolving-insolvency.">http://www.doingbusiness.org/research/resolving-insolvency.</a>

Because the costs of settling up a new business differs by industry also the impact of regulatory market access costs will differ. In order to get better comparability across industries, we haven interacted the OECD Rmaps indicator with the median capitallabour intensity per industry (median over entire observation period and over all size classes). The interaction term therefore is fixed across size class and time.

In the main text we also use data for 1999, bringing the total number of observations at about 2700.

We found evidence for non-constant returns to scale in European business services. Figure A2 shows for eight European business services industries that in 2005 the smallest size classes on average have the highest capital intensity (depreciation per full-time employee). Only in marketing (K744) and architectural and engineering services (K742-3) we find a clear second peak in capital intensity for firms having 50-249 employees.

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 <sup>a)</sup> (x1000 euro)	2000 -2005 a (%) of small total no. of firms		Rclo: Overall cost of closing a business d) 2005	Rmaps: market access costs in prof. services <sup>e)</sup> 2005	Remplad: Flexibility in employment contracts index , 2005
Austria	196	42	243	28.4	91.3	35.6	0.62	0.28	0.42
Belgium	184	76	386	33.8	95.7	28.5	0.37	0.20	0.48
Denmark	96	16	108	37.6	91.4	24.6	0.61	0.11	0.33
Finland	98	16	81	33.2	94.1	33.6	0.38	0.11	0.44
France	240	399	2684	29.7	93.5	24.2	0.49	0.21	0.67
Germany	240	344	3242	28.6	87.0	23.0	0.41	0.27	0.47
Ireland	103	11	70	34.4	91.5	36.4	0.41	0.14	0.24
Italy	240	739	2059	28.0	97.5	53.0	0.75	0.14	0.40
Netherlands	230	104	677	42.1	91.7	24.8	0.40	0.15	0.47
Portugal	193	60	281	12.6	96.2	37.0	0.56	0.23	0.76
Spain	160	378	1918	18.9	95.2	34.7	0.56	0.21	0.65
Sweden	207	141	453	30.4	96.7	43.2	0.56	0.11	0.49
Un.Kingdom	175	426	3234	44.0	91.2	26.8	0.43	0.14	0.16
Total	2362	2751	15436						
Average	182	212	1187	30.9	93.3	30.9	0.50	0.18	0.46

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). e) produced by the OECD Economics Department (Conway and Nicoletti, 2008). 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).

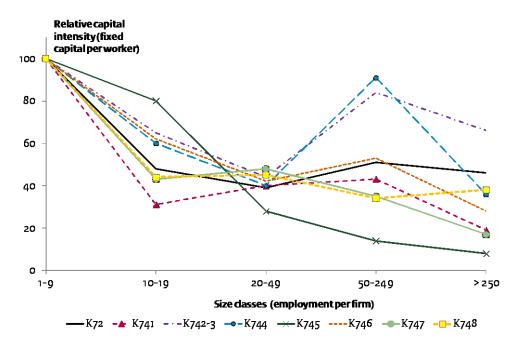
Table A2 Selected industry characteristics of the dataset, average for 13 EU countries, 2000-2005

Industry branch by NACE code <sup>a)</sup>	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.

Figure A2 Relative capital intensity in European business services, 2005, average for 13 EU countries (smallest size class=100)



Legend: K72: IT and computer services; K741: Accountancy, legal, administrative and consultancy services; K742\_3: Architectural and engineering services; K744: Marketing services; K745: Labour recruitment services; K746: Industrial cleaning; K747: Security services; K748: Miscellaneous business services. Data: own calculations using Eurostat New Cronos data.

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