European competitiveness: A semiparametric stochastic metafrontier analysis at the firm level[*]

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Abstract

In this paper a semiparametric stochastic metafrontier approach is used to obtain insight into firm-level competitiveness in Europe. We differ from standard TFP studies at the firm level as we simultaneously allow for inefficiency, noise and do not impose a functional form on the input-output relation. Using AMADEUS firm-level data covering 10 manufacturing sectors from seven EU15 countries, (i) we document substantial, persistent differences in competitiveness (with Belgium and Germany as benchmark countries and Spain lagging behind) and a wide technology gap, (ii) we confirm the absence of convergence in TFP between the seven selected countries, (iii) we highlight the role of post-entry growth for competitiveness.

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1 Introduction

The current eurozone crisis has led to regained interest in national competitiveness issues. First, because in a monetary union, adjustments to external shocks imply adjustments in the domestic economy and, second, because divergences in competitiveness may threaten the stability of the monetary union as such. However, there is much controversy concerning competitiveness indicators. Traditionally, competitiveness has been analyzed from an aggregate point of view, based on the assumption of a representative firm proxied by a sector or economy-wide average. Yet, the recent international trade literature argues that firms behave differently in a given economic environment because of idiosyncratic (marginal cost) heterogeneity, which explains why, for example, international trade is concentrated amongst a small number of highly productive firms. Firm heterogeneity questions the validity of an analysis of competitiveness in terms of a representative firm and rather calls for an analysis at the firm level that provides information about the distribution over all firms within an industry.

At the firm level, competitiveness is defined as the firm's efficiency in using productive resources to supply goods and services, i.e. as *productivity*[1]. Micro-level data permit to assess to what extent industry-level productivity growth can be explained by within-industry dynamics: firm-level productivity growth, reallocation of market shares between existing firms (incumbents) and entry and exit. Bartelsman and Wolf (2013) find that forecasts of macro-level productivity growth based on computed micro-level components (firm-level growth and within-industry reallocation) outperform forecasts based on more aggregate data. Hyytinen and Maliranta (2013) discern a growing awareness among policy-makers that long-term competitiveness and growth may be hampered by inadequate within-industry dynamics.[2]

[1]See Porter (1990), Krugman (1994, p. 35):"*...competitiveness as a poetic way of saying productivity*", OECD (2013, p. 61), European Commission (2013, p. 23 and 31).

[2]The need for firm level data is nicely illustrated by the paradox that Spanish price competitiveness decreased in the 2000-2009 period, but export market shares remained stable (the so called '*Spanish Paradox*'). Antras et al. (2010) show that the puzzle can for a large part be explained by an aggregation

The most complete economic notion of productivity is in terms of total factor productivity (henceforth TFP); i.e. aggregated output over aggregated input. How TFP is best measured is the core of many academic studies (see e.g. Hulten (2000), Van Biesebroeck (2007), Del Gatto et al. (2011) and Van Beveren (2012) for an overview). The parametric non-frontier literature focuses on loosening exogeneity assumptions (on input choice, attrition)[3], recently tackles the omitted price bias[4] and models multi-product firms[5]. The complementary parametric (stochastic) frontier literature (Meeusen and van Den Broeck (1977) and Aigner et al. (1977)) still makes the assumption that inputs in the production function are exogenous, but acknowledge that not the 'average' firm defines technology, but the firms at the boundary of the (pre-whitened) attainable set, resulting in a clear definition of technical efficiency, technical change and technical catch-up[6]. The nonparametric frontier literature in addition makes no or little assumptions on the functional form specification and easily models multiple output-multiple input settings.[7] The traditional nonparametric frontier-based TFP approaches are fully deterministic and thus make a 'no noise' assumption.[8] As it is well-known that any firm-level dataset are often rather noisy, these approaches are inadequate to assess international competitiveness based on firm-level data.

Our first contribution is that we directly address the function misspecification bias, which receives little attention in the standard parametric TFP literature. We cope with the drawback of nonparametric efficiency and TFP approaches, i.e. that noise is a priori ex-

bias; large firms experienced least disadvantageous price competitiveness dynamics and most favorable export dynamics.

[3]See Olley and Pakes (1996), Levinsohn and Petrin (2003) and Ackerberg et al. (2006).

[4]See e.g. Klette and Griliches (1996), Foster et al. (2008) and De Loecker (2011)

[5]See e.g. Bernard et al. (2009).

[6]By the direct definition, contradictory claims are avoided, as in Arnold et al. (2011), who define the production technology by the average firm, but define the technology frontier as the 5% most productive firms.

[7]See Fried et al. (2008) for an overview of nonparametric TFP indices that use distance functions such as the Malmquist index (Caves et al., 1982) and the Hicks-Moorsteen index (Bjurek, 1996).

[8]While recent nonparametric frontier approaches such as the order-m approach of Cazals et al. (2002) and the order-α approach of Aragon et al. (2005) deal with the problems of outliers and extreme noise, they are still deterministic.

cluded from the analysis, by using a semiparametric stochastic frontier-based metafrontier estimation methodology to assess competitiveness. Using AMADEUS firm-level data covering 10 manufacturing sectors from seven EU15 countries, (i) we document substantial, persistent differences in competitiveness and a wide technology gap, (ii) we confirm the absence of convergence in TFP between the seven selected countries, (iii) we quantify the severe competitiveness issues of Spanish firms, (iv) we confirm that the metafrontier is for a large part determined by Belgian firms.

Second, we contribute by exposing *intra-industry dynamics of competitiveness*. We apply a Melitz and Polanec (2012) decomposition on the semiparametric estimates of metafrontier efficiency for seven EU countries to confirm that firm-level productivity growth and reallocation between incumbents is the main driver of industry-level productivity. Further, we show the need to differentiate incumbents by age. It takes time for new firms to raise their technical efficiency. In line with previous studies on firm dynamics, our results indicate that post-entry growth - more than entry and exit as such - explains cross-country differences in industry-level growth and warrant further examination into (institutional) factors that affect post-entry growth.

The remainder of this paper is structured as follows. In section 2, we present the AMADEUS dataset. In section 3, we discuss the measurement of European competitiveness. In section 4, we discuss the intra-industry dynamics of competitiveness in a decomposition analysis. Section 5 concludes.

2 AMADEUS dataset

For our analysis of competitiveness, we use firm-level data as provided by the Bureau van Dijk in the AMADEUS dataset. It is a database of income statements and balance sheets in a common format, elaborated by Bureau van Dijk, based on information gathered from national providers. AMADEUS covers 43 different European countries and in its present version, includes information on 19 million companies[9]. It allows identifying firms by country and sector. For (almost all) the EU15 countries, the covered time horizon goes back to 1996. However, we only use data from 2002 onwards, as before 2002, there were large changes in the number of firms that were sampled in some countries (e.g. Germany).

However, AMADEUS has also some shortcomings. First, despite its wide geographical, time and sectoral range, the sample of firms included can vary considerably, in particular in terms of its composition (rather than in size). The providers of the database rely on national data sources and providers, which are subject to change. In addition, firms that do not provide information for more than three consecutive years are removed from the database, with their entire history. Therefore, indicators derived from this database can show variation caused by sample fluctuations, unrelated to a real change of the indicator, which in an extreme situation may even affect the total time path of the indicator.
Second, while AMADEUS contains comprehensive financial information on a very large number of firms in a comparable format, it lacks information on firms' characteristics (like export behavior, innovation effort) that allow to understand the patterns in key financial variables or variables derived thereof (profits, value added,...). For the latter, access to and a link with other information sources is required.

Still, AMADEUS seems the most adequate data source[10] for a firm-level competitiveness analysis. To correct as much as possible for the variability in sample composition, we keep the availability over time as consistent as possible by compiling in one database the information provided in each issue of AMADEUS, keeping systematically for each year within the time range (1996 and onwards) the last available information. In this way, we reintroduce into the database the firms that were dropped, because of changes in national data providers or other reasons why firms stopped providing information for three consecutive years. As a consequence, each firm is kept in the database with the longest possible time series of data. In addition, coverage is improved in this way, evidently,

[9] See http://www.bvdinfo.com/Products/Company-Information/International/AMADEUS.aspx.
[10] We compared AMADEUS to EFIGE and MICRO-DYN

without reaching a comparable level (overall) as the structural business surveys.

As the advocated methodology is kernel-based, it remains vulnerable for the so called curse of dimensionality. Therefore, we only include countries that have at minimum approximately 50 observations per year and per sector. We selected seven countries and 10 nace 2-digit sectors for which we have at least 50 firm-level observations to compute a country frontier and metafrontier for the interval 2002-2009 (see Table 1).

Table 1: Selected countries and sectors

Selected countries	
Belgium, Germany, Spain, Finland, France, United Kingdom and Italy	
Selected Nace rev. 1.1 sectors	
NACE 15:	Manufacture of food products and beverages
NACE 17:	Manufacture of textiles
	manufacture of articles of straw and plaiting materials
NACE 22:	Publishing, printing and reproduction of recorded media
NACE 24:	Manufacture of chemicals and chemical products
NACE 25:	Manufacture of rubber and plastic products
NACE 26:	Manufacture of other non-metallic mineral products
NACE 28:	Manufacture of fabricated metal products, except machinery and equipment
NACE 29:	Manufacture of machinery and equipment n.e.c.
NACE 31:	Manufacture of electrical machinery and apparatus n.e.c.
NACE 36:	Manufacture of furniture; manufacturing n.e.c.

Deflated value added is chosen as measure of firm output[11], whereas indicators of factor

[11]For our estimation of technical efficiency the output of firms has been deflated using national industry-level price indices. The firm-level output volumes, expressed as value added in constant prices, do not take into account possible differences in price levels between countries. This may affect the comparison of efficiency levels across countries. Purchasing power parities (PPP) could provide volumes that account for these price differences. Sonderman (2012) uses OECD-Eurostat PPPs to compute PPP-adjusted productivity levels based on EUKLEMS data for the period 1970-2007. In manufacturing, out of the 12 EU countries considered, Belgium follows Ireland with the highest PPP-adjusted productivity. The ranking of the other countries is rather similar to the ranking based on our estimation though Finland seems to perform better when considering PPP-adjusted productivity. Italy and Spain clearly lag Belgium, Finland, France and Germany in terms of PPP-adjusted productivity. Sonderman (2012) points out that the use of PPPs implies some strong assumptions. PPPs are only available on an aggregate level, e.g. only for manufacturing as a whole. Applying PPPs to individual sectors assumes that the evolution of price levels is similar in all sectors to the evolution in manufacturing as a whole, an assumption that is clearly refuted by the data. Moreover, if differences in the prices of similar products reflect differences in quality it is not clear whether the differences in output prices should be discarded.

inputs are obtained from the information on the number of persons employed and the value of deflated fixed assets.[12] Extreme noise and insensible data were eliminated, while allowing firms to vary considerably in competitiveness[13].

The final dataset consists in total of 620,342 observations of 140,595 firms. Descriptive Table 2 illustrates that there is considerable heterogeneity in sample size between countries and sectors. In terms of observations and firms, the sector *'Manufacture of fabricated metal products, except machinery and equipment'* is the largest with 150,357 observations of 35,308 firms, while sector 'Manufacture of electrical machinery and apparatus n.e.c.' is the smallest, with 29,359 observations of 6,822 firms.

We use national industry-wide deflators as data on firm-level prices are unavailable. We examined the potential effects of ignoring within-industry output price heterogeneity for a sample of Belgian firms (see Appendix H). We notice that using sector-price deflated revenue to proxy for firm-level output results in a bias of the semiparamatric estimates of efficiency. However, we do not find many indications that this bias is systematically linked to input factors or other firm characteristics (e.g., age or export status).

[12] All in euro.

[13] To avoid effects of extreme outliers and extreme noise in the whole dataset, we limit the sample to observations with at least five employees, deflated value added per employee smaller than 1,000,000 euro, deflated value added per employee at least 100 euro, deflated tangible fixed assets at least 1,000 euro, the number of months in a book year equal to 12 and growth rates of input and output lower (higher) than 10 (-10). As our estimation methodology is sensitive for extremely large observations, we delete for the two inputs and deflated value added, the top 1% percentile per year per sector. Additionally, insensible labor-capital combinations are removed by deleting the top and bottom percentile of Labour use/Deflated tangible assets per year per sector. Further, we deleted the bottom percentile of Deflated Added Value over Deflated Tangible Fixed assets and Deflated Added Value over Number of employees to eliminate obvious cases of erroneous reporting.

Table 2: Summary table I

Number of observations per country per sector								
Nace	BE	DE	ES	FI	FR	GB	IT	Total
15	3043	5350	34573	2242	12044	5679	21290	84221
17	1148	1408	10411	503	3094	1992	17275	35831
22	1312	3888	18628	2693	6685	5843	12534	51583
24	1866	3743	10317	527	3609	4705	11325	36092
25	817	4581	12293	1286	4800	3438	15163	42378
26	1449	2824	20089	1044	3662	1694	16381	47143
28	2321	10371	49348	5958	17014	8198	57147	150357
29	1497	11846	17832	3617	7733	4677	41703	88905
31	587	3317	5608	962	2362	3071	13452	29359
36	804	2345	18189	1783	3557	6346	21449	54473
Total	14844	49673	197288	20615	64560	45643	227719	620342
Number of firms per country per sector								
Nace	BE	DE	ES	FI	FR	GB	IT	Total
15	534	1636	6481	477	3053	1357	4752	18290
17	221	487	2092	122	821	525	4051	8319
22	253	1400	3634	629	1705	1630	2965	12216
24	331	1084	1780	121	793	1081	2167	7357
25	145	1462	2204	254	1115	899	3182	9261
26	268	931	3616	207	783	420	3742	9967
28	444	3804	9390	1299	3930	2179	14262	35308
29	276	3682	3287	790	1831	1183	9158	20207
31	109	1034	1056	203	524	810	3086	6822
36	146	781	3598	379	949	1692	5303	12848
Total	2727	16301	37138	4481	15504	11776	52668	140595
Number of observations per country per year								
Nace	BE	DE	ES	FI	FR	GB	IT	Total
2002	1985	2359	26080	2750	11467	8135	33210	85986
2003	1949	3616	26283	2860	10336	7183	30364	82591
2004	1896	4562	26330	2759	9069	5762	28639	79017
2005	1847	7391	26311	2719	8223	5191	17987	69669
2006	1906	8850	26548	2756	7304	5069	27846	80279
2007	1904	8295	25350	2733	6560	5127	29307	79276
2008	1809	7527	20735	2242	5952	4695	32699	75659
2009	1548	7073	19651	1796	5649	4481	27667	67865
Total	14844	49673	197288	20615	64560	45643	227719	620342

Table 3 illustrates that size distributions of sampled firms are heterogeneous over countries. In particular, in Belgium, Germany and the UK, firm size, measured in terms of labor use, capital use or value added, is significantly higher than in Spain, Finland, France and Italy. This bias is especially substantial for Germany and the UK (see also Dall'Olio et al. (2013)). Bartelsman et al. (2009) point out that cross-country comparisons of firm dynamics are hampered by definitional problems as well as measurement problems due to differences in coverage, unit of observation, classification of activity and data quality. In constructing a database on firm dynamics for EU countries, MICRO-DYN (2007) assessed the extent to which AMADEUS covers the total population of firms, as reflected in the Structural Business Statistics (SBS), provided by Eurostat. It is pointed out that AMADEUS is not a census nor based on a representative sample and tends to be biased towards larger firms (see Appendix B). Differences between countries in coverage, reporting requirements and sampling are likely to affect our analysis, especially regarding entry and exit, discussed below, for which - out of necessity- a second best definition is applied. Dall'Olio et al. (2013) point out that as not all firms in AMADEUS report the input and output data, the sample of firms for which productivity can be measured may not be representative of the total population of firms in a country.

To limit the effects of different sampling of firms (in terms of firm size) between countries, we perform extensive sensitivity tests (i.e., subsampling, differing weights) on the competitiveness estimates.

Table 3: Summary table II

Labour use in persons

	Mean	St.Dev	Min	25%	Med	75%	Max
BE	111.67	161.51	5.00	32.00	56.00	119.00	2514.00
DE	138.69	175.69	5.00	45.00	86.00	162.00	3186.00
ES	38.60	80.06	5.00	10.00	18.00	35.00	2392.00
FI	58.49	128.85	5.00	10.00	20.00	48.00	3015.00
FR	63.45	129.35	5.00	12.00	25.00	56.00	2786.00
GB	156.54	218.15	5.00	49.00	86.00	173.00	3619.00
IT	47.52	94.97	5.00	11.00	21.00	46.00	3530.00

Deflated Tangible Fixed Assets (in 1000 euro)

	Mean	St.Dev	Min	25%	Med	75%	Max
BE	4702.98	10746.48	1.78	625.74	1711.43	4303.74	269999.32
DE	4403.62	8881.85	1.00	426.24	1676.49	4581.74	232727.78
ES	1522.52	5652.53	1.00	90.03	289.38	937.54	252330.43
FI	2000.60	7928.14	1.12	118.03	362.02	1253.73	326118.05
FR	1510.84	5811.24	1.01	57.06	195.23	791.70	246235.76
GB	4476.73	11823.50	1.05	487.13	1425.67	3759.27	331387.85
IT	1851.16	5556.23	1.02	117.92	437.07	1495.94	256738.86

Deflated Added Value (in 1000 euro)

	Mean	St.Dev	Min	25%	Med	75%	Max
BE	8700.40	10746.48	31.04	1960.00	3675.85	8359.09	311565.45
DE	8758.82	8881.85	2.41	2332.94	4735.89	9462.15	292744.27
ES	1694.37	5652.53	1.22	263.04	518.18	1185.29	271084.19
FI	3364.92	7928.14	12.41	433.93	895.14	2425.12	239061.17
FR	3833.13	5811.24	5.94	507.52	1145.87	2884.79	373672.39
GB	6386.56	11823.50	0.87	1539.47	2889.08	6145.40	279228.22
IT	2617.19	5556.23	2.92	426.94	875.04	2182.06	376926.21

3 Measuring competitiveness: A semiparametric stochastic metafrontier analysis at the firm-level

3.1 Introduction

Recently, various stochastic semiparametric frontier approaches are introduced that allow for noise and do not impose a priori assumptions on the function form between inputs and output. The most flexible one is the local maximum likelihood approach of Kumbhakar et al. (2007) that localizes the stochastic frontier via kernel weighting. Simar and Zelenyuk (2011) proposed to monotonize (and convexify) the Kumbhakar et al. (2007) frontier in a stochastic FDH (DEA) approach.[14] The localized frontier approaches are semiparametric, as they only require a priori distributional assumptions on the convolution term of the anchorage model to separate noise from inefficiency.
A competitiveness index based on a stochastic semiparametric frontier is up to now non-existent, and is exactly what we advocate to assess international competitiveness with firm-level data.

We contribute to the literature on the estimation of metatechnology[15] by introducing a stochastic *metafrontier* competitiveness index that does not imposes a priori a functional form. In particular, to assess international competitiveness with firm-level data, we first define the country-specific sectoral frontiers and secondly a sectoral stochastic metafrontier

[14]Kuosmanen and Kortelainen (2012) proposed the use of convex least squares to construct the Stochastic Non-Smooth Envelopment of Data (StoNED) approach and Martins-Filho and Yao (2013) introduced profile likelihood estimation to construct a semiparametric stochastic profile likelihood frontier estimator. The localized frontier approaches are the only approaches that do not need a priori parametric assumptions to allow for heterogeneity in the convolution term.

[15]The literature on metafrontier estimation starts with Battese and Rao (2002), who proposed a stochastic parametric metafrontier approach. Battese et al. (2004) improved the analysis by ensuring that the stochastic metafrontier always envelops the group frontiers. O'Donnell et al. (2008) introduced nonparametric deterministic metafrontier estimation. Dynamic versions, based on the Malmquist index and its decompositions are proposed by Oh and Lee (2010) and Chen and Yang (2011).

which envelops the country-specific frontiers. Based on the stochastic metafrontier, we define metafrontier efficiency as a measure of the level of international competitiveness and metafrontier Hicks-Moorsteen TFP as a measure of the dynamics of firm competitiveness.

We apply the advocated methodology on firm-level balance sheet data of manufacturing firms as provided by the Bureau van Dijk in the AMADEUS dataset 1) to test for existence of convergence between seven selected EU15 countries in the period 2002-2009 for 10 nace 2-digit manufacturing sectors and 2) to obtain new insight into the intra-industry dynamics of competitiveness.

Our main findings include that 1) semiparametric frontier-based estimates confirm the persistent, substantial differences in competitiveness and the absence of convergence in TFP between the seven selected countries, 2) it is crucial for competitiveness that the right conditions exist to let entering firms become more efficient over time. Our results are complementary to the results from MICRO-DYN, EFIGE and COMPNET as we directly deal with the function misspecification bias and allow for inefficiency.

3.2 Methodology

3.2.1 Level on competitiveness: metafrontier efficiency

To assess the level of competitiveness at the firm level, we make use of metafrontier efficiency estimation.

The basis of nonparametric efficiency estimation is the distance function, introduced by (Farell (1957) and Debreu (1951)). To calculate distance functions in country z, we start from the definition of a production set Ψ_z, frontier $\mathbf{y}^{\partial_z}$ and inefficiency λ_z as a distance to the country frontier.[16] Assume that producers in country z use a heterogeneous non-negative input vector $\mathbf{X} \in \mathbf{R}_+^p$ to produce a heterogeneous multivariate output vector

[16]Although the outline is limited to the output-oriented case, the extension to input-orientation is straightforward.

$\mathbf{Y} \in \mathbf{R}^q_+$. The production set Ψ_z of feasible input-output combinations can be defined as:

$$\Psi_z = \{(\mathbf{X}, \mathbf{Y}) | Z = z,\ \mathbf{X} \text{ can produce } \mathbf{Y}\}. \tag{1}$$

Farell (1957) and Debreu (1951) were the first to acknowledge that the output-oriented efficiency score (i.e., maximization of outputs $\mathbf{y}$ given the observed inputs $\mathbf{x}$) of an observation $(\mathbf{x}, \mathbf{y})$ can be obtained as:

$$\lambda_z(\mathbf{x}, \mathbf{y}|z) = \sup\{\lambda | (\mathbf{x}, \lambda\mathbf{y}) \in \Psi_z\}. \tag{2}$$

A value $\lambda(\mathbf{x}, \mathbf{y}) = 1$ indicates full technical efficiency (i.e., there are no observations which are able to produce more outputs for the given input set). A $\lambda(\mathbf{x}, \mathbf{y}) > 1$ indicates inefficiency, i.e., it is possible to have a radial increase of $\lambda(\mathbf{x}, \mathbf{y})$ in all the outputs in order to reach the efficient frontier. For a given level of input and a given output mix, the efficient level of output is given by:

$$\mathbf{y}^{\partial_z}(\mathbf{x}, \mathbf{y}) = \lambda_z(\mathbf{x}, \mathbf{y})\mathbf{y}. \tag{3}$$

Distance function $D_z(\mathbf{x}, \mathbf{y})$ is the inverse of inefficiency $\lambda_z(\mathbf{x}, \mathbf{y})$.

The metaproduction set, which assumes that all countries z operate under the same technology, is defined by Ψ:

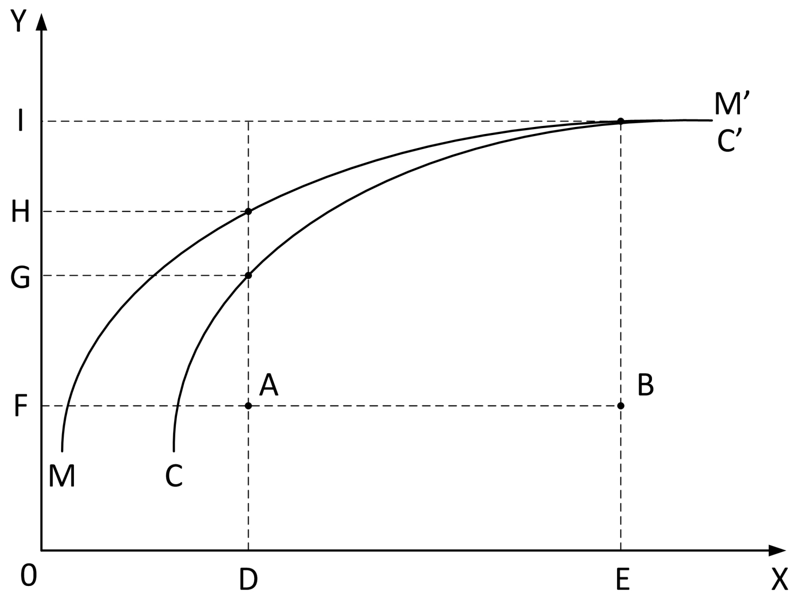
$$\Psi = \bigcup_{z \in Z} \Psi_z. \tag{4}$$

Analogously as in (2) and (3), the metafrontier $\mathbf{y}^{\partial}(\mathbf{x}, \mathbf{y})$ and metafrontier efficiency $D(x, y)$ based on Ψ are defined. The technology gap ratio, which denotes the technology disadvantage, is defined as $TGR = D(x, y)/D_z(x, y) \leq 1$. Values of $TGR < 1$ denote that the country technology is less advanced in comparison to the metatechnology.

Illustration Figure 1 illustrates the concepts technical efficiency $D_z(x, y)$, metafrontier efficiency $D(x, y)$ and technology gap ratio TGR. Observation A and B which use respectively $|0D|$ and $|0E|$ input to produce $|0F|$ output in country C, with country-specific frontier CC'. Observation A is technically more efficient than B ($D_C(x_A, y_A) =$

$|0F|/|0G| > D_C(x_B, y_B) = |0F|/|0I|)$, and also more competitive as its metafrontier efficiency is higher $(D(x_A, y_A) = |0F|/|0H| < D(x_A, y_A) = |0F|/|0I|)$. While for $X < |0E|$, the country is characterized by a technological deficit in comparison to the meta-technology $(TGR_A = |0G|/|0H| < 1)$, for $X \geq |0E|$, country C has the benchmark technology $(TGR_B = |0I|/|0I| = 1)$.

Figure 1: Metafrontier estimation



3.2.2 Dynamics of competitiveness: metafrontier TFP change

To capture the dynamics of competitiveness, we focus on TFP change, which captures metafrontier efficiency change, but also scale efficiency change and technical change. Assume a firm k with 1 input x and 1 output y. The change in productivity with period t as base year is defined in (5). In a 1 input - 1 output case, productivity can thus easily be calculated, using the observed output and input quantities. However, usually, production is characterized by multiple inputs that are used to produce 1 or more outputs.

$$\prod_k^t = \frac{AP_k^{t+1}}{AP_k^t} = \frac{\frac{y_k^{t+1}}{x_k^{t+1}}}{\frac{y_k^t}{x_k^t}} \tag{5}$$

Caves et al. (1982) have shown that multivariate nonparametric distance functions can be used in a Malmquist productivity framework to estimate TFP change in a multidimensional setting. The index has shown its value in numerous of publications, starting with Färe et al. (1994), but has as main disadvantage that it is incomplete, which means that it cannot always be interpreted as a measure of TFP. The popular Malmquist index can only be regarded as an index of Total Factor Productivity when the assumption of CRS technology with inverse homotheticity holds (O'Donnell, 2012), which restricts its usefulness for competitiveness comparisons over different sectors with firm-level data.

In contrast, the Hicks-Moorsteen TFP index of Bjurek (1996)[17] is well-defined under general assumptions of variable returns to scale and strong disposability (Epure et al., 2011). The Hicks-Moorsteen TFP index directly measures the ratio of aggregated output to aggregated input. Until recently, the Malmquist index was the only index that could be decomposed meaningfully in Technical Change and Efficiency Change. See Färe et al. (2008) for a review of the many decompositions of the Malmquist index. This explains why the Malmquist productivity index is more popular than other productivity indices such as the Hicks-Moorsteen TFP index that are complete (i.e., always equal to TFP). Recently, O'Donnell (2012) showed that any complete TFP index can be meaningfully decomposed and operationalized the decompositions in a DEA framework. We do not decompose TFP change as this goes beyond the scope of this paper and we do not wish to impose convexity (and thus estimate a pre-whitened Free Disposal Hull instead of a pre-whitened DEA frontier).

[17] Bjurek (1996) somewhat confusingly called it the Malmquist TFP index.

Figure 2: Hicks-Moorsteen Index

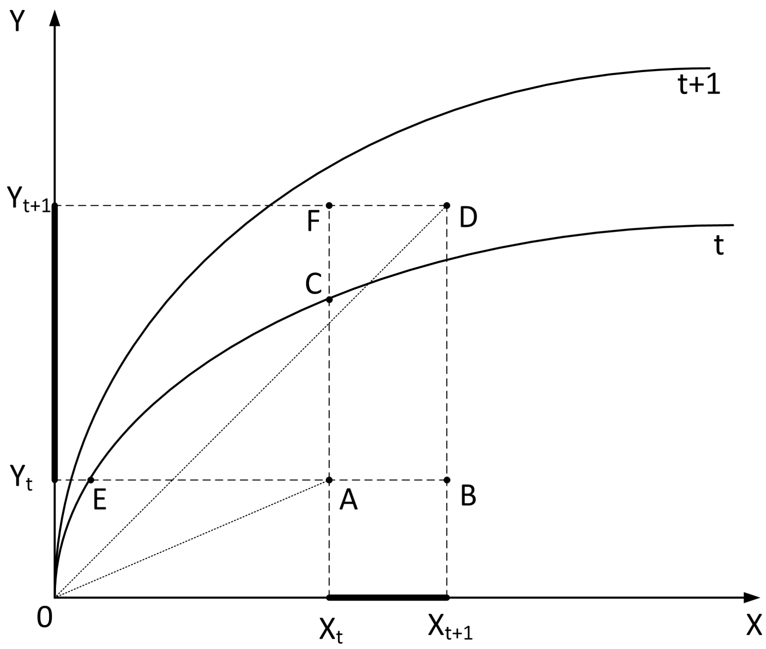


Figure 2, based on Epure et al. (2011), illustrates the definition of the Hick-Moorsteen index for a technology with decreasing returns to scale. The change of TFP with base year t is $|x_tF|/|x_tA|$ divided by $|y_tB|/|y_tA|$. This can be formulated as the ratio of distance functions as shown in (6). In contrast to the Malmquist index, the Hicks-Moorsteen index does not depend on an a priori choice between an output-orientated view (i.e., maximizing output, given input) or an input-oriented view (i.e., minimizing input, given output). In particular, the Hicks-Moorsteen is the ratio of aggregated output changes (captured by the ratio of output-oriented distance functions) to aggregated input changes (captured by the ratio of input-oriented distance functions).

$$
\begin{aligned}
\prod_k^t &= \frac{|FA|}{|BA|} \\
&= \frac{X_t F / X_t A}{Y_t B / Y_t A} \\
&= \frac{(X_t F / X_t C)/(X_t A / X_t C)}{(Y_t B / Y_t E)/(Y_t A / Y_t E)} \\
&= \frac{D_t^o(Y_{t+1}, X_t)/D_t^o(Y_t, X_t)}{D_t^i(Y_t, X_{t+1})/D_t^i(Y_t, X_t)} = HMTFP_t
\end{aligned}
\tag{6}
$$

In (6), we considered year t as reference year to calculate TFP changes. However, also year t+1 could be chosen as reference year. To make no arbitrary choice of the reference technology, the Hicks-Moorsteen index of productivity change, which we use to measure the dynamics of competitiveness, is defined as the geometric average of the HMTFP with respectively year t and t+1 as reference year (see (7)).

$$
\begin{aligned}
HMTFP &= (HMTFP_t \times HMTFP_{t+1})^{1/2} \\
&= \left(\frac{D_t^o(y_{t+1}, x_t)/D_t^o(y_t, x_t)}{D_t^i(y_t, x_{t+1})/D_t^i(y_t, x_t)} \times \frac{D_{t+1}^o(y_{t+1}, x_t)/D_{t+1}^o(y_t, x_t)}{D_{t+1}^i(y_t, x_{t+1})/D_{t+1}^i(y_t, x_t)} \right)^{1/2}
\end{aligned}
\tag{7}
$$

3.2.3 Stochastic FDH frontier estimation

In any large-scale dataset of micro-economic units, like households or firms, there is measurement and random variation. As a result, the assumption that there is no noise as implicitly made in DEA and FDH is difficult to maintain. To obtain reliable nonparametric estimates of metafrontier efficiency and TFP change, we need to estimate distance functions that are stochastic.

Parametric stochastic frontier approaches have been developed specifically to accommodate noise in the data generation process. To smoothly decompose noise from inefficiency, standard stochastic frontier analysis (SFA) however imposes (1) the functional form of the frontier (e.g., Cobb-Douglas, translog, Fourier), (2) the distribution of noise and (3) the distribution of inefficiency (e.g., half-normal, truncated normal, exponential, gamma).

However, a survey by Yatchew (1998) indicates that economic theory almost never defines a specific functional form of a production function. As such, imposing an arbitrary functional specification of the production frontier can result in erroneous inference, which in turn biases the estimates and makes the analysis intricate. Even the translog specification, which is a flexible parametric second-order local approximation of any functional form, can give economically unreasonable estimates. In some cases, the translog specification does not capture all nonlinearities in the true model (Henderson and Kumbhakar, 2006) and implies high multicollinearity as result of the inclusion of quadratic effects and interactions. As the translog function is known to violate regularity conditions within the data region, it is only appropriate under strict assumptions on the elasticity of substitution (see e.g Barnett (1985) and Barnett et al. (1985)).

Kumbhakar et al. (2007) proposed an alternative approach to loosen simultaneously the *a priori* assumptions on (1) the specification of the frontier, (2) the distribution of inefficiency and (3) the distribution of noise. They propose to localize the parametric stochastic frontier model, based on the local maximum likelihood approach of Tibshirani and Hastie (1987) and Fan et al. (1996). The resulting local maximum likelihood approach to estimate the stochastic frontier localizes the specification of the global frontier. Additionally, the approach is robust for unknown heteroskedasticity in both noise and inefficiency. The Kumbhakar et al. (2007) method makes the parameters of a parametric model dependent on the covariates via a process of localization. In result the marginal frontier impact of inputs can be estimated for each data point.[18]

A direct implication of localization is that the frontier can be non-monotone or non-concave. Monotone, multivariate and concave estimates of nonparametric stochastic frontier can

[18]The value of the LMLSF approach is shown in recent applications. Kumbhakar et al. (2007) have used the LMLSF approach to analyze the cost function of a random sample of 500 U.S. commercial banks. Additionally, Kumbhakar and Tsionas (2008) have applied the approach to estimate stochastic cost frontier models for a sample of 3691 U.S. commercial banks, while Serra and Goodwin (2009) use the approach to compare efficiency ratings of organic and conventional arable crop farms in the Spanish region of Andalucía.

easily be achieved as shown in Simar and Zelenyuk (2011).[19] They propose a two-step approach where the cloud of data points is pre-whitened from noise by a nonparametric stochastic frontier in the first step and inefficiency is measured as a distance to the pre-whitened frontier in a second step. Free disposability or concavity are imposed by applying respectively Free Disposal Hull (FDH) or Data Envelopment Analysis (DEA) in the second step, i.e. after correcting for stochastic noise. However, the stochastic FDH/DEA approach implies (1) remaining distributional assumptions on inefficiency and noise for the anchorage model and (2) a high computational burden.

This section briefly reviews the estimation of a stochastic FDH/DEA model. Our overview starts from the Kumbhakar et al. (2007) model with univariate output and multivariate input. Full details can be found in Kumbhakar et al. (2007), Simar and Zelenyuk (2011) and Park et al. (2010).

We consider a set of i.i.d. random variables $(\mathbf{X}_i, \mathbf{Y}_i)$, for $i = 1, ..., n$, with input $\mathbf{X}_i \in \Re^p_+$ and output $Y_i \in \Re^1_+$. The local maximum likelihood is based on a local parametric anchorage model. Typically, the frontier function $r(\mathbf{X})$ is introduced as in the parametric model of Aigner et al. (1977):

$$\log Y_i = r(\mathbf{X}_i) - u_i + v_i \text{ , with } i = 1, ..., n. \tag{8}$$

The inefficiency term $\mathbf{u}$ is in this work specified to have a half normal distribution ($\mathbf{u} \sim |N(0, \sigma^2_{\mathbf{u}}(\mathbf{x})|)$), the error term $\mathbf{v}$ is normally distributed ($\mathbf{v} \sim N(0, \sigma^2_{\mathbf{v}}(\mathbf{x}, \mathbf{z}))$) and $\mathbf{u}$ and $\mathbf{v}$ are independent conditionally on $(\mathbf{X})$.[20] The conditional probability distribution function (pdf) for $\mathbf{Y}$ given $(\mathbf{X})$: $pdf(\mathbf{y}|\mathbf{x}) = g(\mathbf{y}, r(\mathbf{x}), \tau(\mathbf{x}))$, where $r(\mathbf{x})$ and $\tau(\mathbf{x})$ - which is the pair $(\sigma^2_{\mathbf{u}}(\mathbf{x}), \sigma^2_{\mathbf{v}}(\mathbf{x}))$ - are to be estimated and g is assumed to be known. The basic idea of

[19] Simar and Zelenyuk (2011) also extends the Kumbhakar et al. (2007) approach to the full multivariate model without imposing parametric assumptions on the production relationship by the use of polar coordinates as in Simar (2007).

[20] Note however that this assumption is hard. Smith (2008) shows that the stochastic frontier estimates are significantly biased if the error component dependence is incorrectly ignored.

the nonparametric stochastic frontier approach is to use a local polynomial approximation to estimate the unknown local factors $r(\mathbf{x})$ and $\boldsymbol{\tau}(\mathbf{x})$, which determine the conditional log-likelihood function as defined in (9).

$$L(r, \boldsymbol{\tau}; \mathbf{X}) = \sum_{i=1}^{n} \log\, g(Y_i, r(\mathbf{X}_i), \boldsymbol{\tau}(\mathbf{X}_i)). \tag{9}$$

The choice of the order of polynomials is discussed in Park et al. (2008). The authors found by simulation that in local likelihood estimation, first order polynomials are preferred when the interest is in the fitted value and second order polynomial terms are preferred if the interest is in the first derivatives. As we are interested in the frontier fit and inefficiency, but not in the effect of inputs on the inefficiency and noise distribution per se, we restrict the model to a localized Cobb-Douglas model (i.e., Local Linear Maximum Likelihood Estimation).

As discussed above, localization implies that we do not impose that a parametric form of the frontier and homogeneity in $\boldsymbol{\epsilon} = \mathbf{v} - \mathbf{u}$ holds for all units, but only locally, for units with a similar operating environment.

Gaussian kernel weight functions l^c as defined in (10) for $\mathbf{x}_k$ are used to give more weight to observations near the observation point. Window widths $\mathbf{h}$ determine the window of localization. If the window is very large, all observations are considered to be similar and we return to the parametric case with a linear frontier and no heterogeneity in $\boldsymbol{\epsilon}$. If the window width is small, only some observations are considered to be similar to the observation. Non-linearities in the frontier and heterogeneity in $\boldsymbol{\epsilon}$ are allowed. To allow for multivariate $\mathbf{X}$, we define -as is common practice - a product kernel $K_{\mathbf{h}}(\mathbf{X}_i, \mathbf{x}) = \prod_{k=1}^{q}(h_k)^{-1} l^c((X_{ik} - x_k)/h_k)$.

$$l^c\left(\frac{X_{ik} - x_k}{h_k}\right) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{X_{ik} - x_k}{h_k}\right)^2}. \tag{10}$$

The localization of the conditional log-likelihood of the stochastic frontier model in direction of $\mathbf{X}$ is defined in (11). By maximization of the localized conditional log-likelihood function, $\hat{r}(\mathbf{x}) = \hat{r}_0 + \hat{r}_1(\mathbf{X}_i - \mathbf{x})$ and $\hat{\boldsymbol{\tau}}(\mathbf{x}) = \hat{\boldsymbol{\tau}}_0 + \hat{\boldsymbol{\tau}}_1(\mathbf{X}_i - \mathbf{x})$ are obtained (see (12)).

$$L_n(r_0, r_1, \boldsymbol{\tau}_0, \boldsymbol{\tau}_1; \mathbf{X},)$$
$$= \sum_{i=1}^{n} \log g(Y_i, r_0 + r_1(\mathbf{X}_i - \mathbf{x}), \boldsymbol{\tau}_0 + \boldsymbol{\tau}_1(\mathbf{X}_i - \mathbf{x}))K_{\mathbf{h}}(\mathbf{X}_i - \mathbf{x}). \tag{11}$$

$$(\hat{r}_0, \hat{r}_1, \hat{\boldsymbol{\tau}}_0, \hat{\boldsymbol{\tau}}_1) = \arg \max_{r_0, r_1, \boldsymbol{\tau}_0, \boldsymbol{\tau}_1} L_n(r_0, r_1, \boldsymbol{\tau}_0, \boldsymbol{\tau}_1; \mathbf{X},). \tag{12}$$

The choice of multivariate bandwidth $\mathbf{h}$ is of crucial importance. We opt for the often used data-driven approach that minimizes the asymptotic integrated mean squared error (AIMSE): the least-squares cross-validation approach as defined in (13). We estimate an optimal value of $\mathbf{h}$ by least squares cross-validation for a wide grid of values of $\mathbf{h}$.

$$CV(\mathbf{h}) = \frac{1}{n} \sum_{i=1}^{n} ((\log Y_i - (\hat{r}_0^{(i)}(\mathbf{X}_i) - \hat{u}_i^{(i)}))^2 t, \tag{13}$$

where $\hat{r}_0^{(i)}$ and $\hat{u}_i^{(i)}$ are the leave-one-out version of the local linear estimators and $0 \leq t \leq 1$ is a trimming weight to limit the sensitivity of the routine to potential numerical problems and outlying values.

Simulations of Simar and Zelenyuk (2011) show that the distributional assumptions in the anchorage model are not restrictive for the frontier fit. However, as the individual efficiency scores are highly sensitive for distributional assumptions on the convolution term $\boldsymbol{\epsilon} = \mathbf{v} - \mathbf{u}$, Simar and Zelenyuk (2011) propose to not decompose the convolution term $\boldsymbol{\epsilon} = \mathbf{u} - \mathbf{v}$. The authors propose a two-step procedure where in a first step the nonparametric stochastic frontier model pre-whitens the frontier and where in a second step stochastic versions of FDH/DEA estimators are derived. In other words, the authors propose to estimate $\widetilde{\lambda}_i = exp(\widetilde{u_i - v_i})$, where the wide tilde denotes that FDH (DEA) is used to obtain a (convex) free disposable hull of the estimated nonparametric frontier. We focus on stochastic FDH as we do not which to add the assumption of convexity of the frontier.

3.3 Results

3.3.1 Computation

For each of the 10 selected Nace rev. 1.1. sectors, in a first step, we estimate the seven country-specific stochastic FDH frontiers for each year in the period 2002-2009 and defined the metafrontier as the Free Disposal Hull of the country-specific frontiers.[21] In a second step, we obtained estimates of (i) the level of competitiveness by estimating metafrontier efficiency as the distance of a firm to the metafrontier, the technology gap ratio, which compares the country-specific technology boundary with the metafrontier technology boundary, (ii) the dynamics of competitiveness by estimating TFP change by a Hicks-Moorsteen index, based on the estimated stochastic FDH metafrontiers.

As any sector has its own specificities, we do not aggregate the sectors in the discussion of the results. We rather focus on the largest sector, '*Manufacture of fabricated metal products, except machinery and equipment*' and provide results for all 10 sectors in the Appendix A. We discuss this sector (i), because, given the abundance of observations in this sector, estimates are most reliable for this sector and in any case not influenced by the so called '*curse of dimensionality*', (ii) because the results of this sector are in line with the general picture of results that we found in the vast majority of sectors studied.

3.3.2 Level of competitiveness

Figure 3 shows the weighted median metafrontier efficiency of each country in each year. Firms are weighted by value added to take into account varying importance of firms in

[21]The procedure implies that the likelihood function needs to be optimized for each observation. As optimizing bandwidth sizes implies that the routine runs in its leave-one-out version over hundred times (in our case 300 times), this approach is computationally very cumbersome. By making use of parallel programming techniques and running the code on the High Performance Computing network of Ghent University, we were able to estimate the localized stochastic frontier for all the 560 cases (10 sectors, 7 countries, 8 years). As numerical issues are a priori hard to exclude in observation-specific optimization, we removed outliers when estimating the Free Disposal Hull of the frontier fit. Code in R available upon request.

the industry. Overall, Belgium and Germany have highest metafrontier efficiency, followed by France, Italy, and Finland. The low performers are the UK[22] and especially Spain in recent years. In all countries, metafrontier efficiency is declining since 2006, indicating that a small group of high performing firms, that define the frontier technology, are diverging from the other firms. In line with Baily et al. (1992), Bartelsman and Doms (2000) and Syverson (2011), we find that competitiveness differences are persistent and substantial. In pre-crisis 2007, half of the firms in Belgium are estimated to be able to increase revenues with 20 percent, given input, while Spanish firms are estimated to be able to double revenues, given input. Figure 4, discussed in detail below, shows that this performance gap finds its origin mainly in substantial technological differences.

Given the documented firm heterogeneity (discussed in the Introduction), a representative (median or average) firm provides only an imperfect indication of the actual competitiveness stance. A more appropriate alternative is to test for domination of distributions of firm competitiveness (change). We use stochastic dominance tests[23], based on Davidson and Duclos (2012), to assess whether the (cumulative) distribution of metafrontier efficiency in a country dominates the (cumulative) distribution of metafrontier efficiency in another country. The approach of Davidson and Duclos (2012) starts from non-dominance as the null hypothesis (which differs from standard practice). This has as main merit that it implies that, if we succeed in rejecting the null, the other possibility is dominance, en-

[22] EU KLEMS data (http://www.euklems.net) of industry-level TFP show that of the group of seven countries that we consider, the UK and Spain are clearly dominated by the other countries in manufacturing industries in the period 2003-2007, whereas Belgium and France had the highest average TFP levels. A first assessment of TFP in COMPNET indicates that the TFP level of Belgium was higher over the period 2000-2009 than in Germany and France (Angeloni and Bernatti, 2012). Analysis of the EFIGE data show that over the period 2001-2009 Germany and France perform substantially better than Italy, Spain and the UK in terms of TFP (Altomonte et al., 2012). See also European Commission (2013), wherein the low productivity of the UK manufacturing sector and high productivity of the UK service sector is described.

[23] See e.g. Asplund and Nocke (2006) for an application of stochastic dominance testing with firm-level data.

abling us to draw the conclusion of dominance.[24] Table 4 shows the number of years in the period 2002-2009 we can reject non-dominance at the 5% signifance level and thus *accept* dominance between countries. In particular, Table 4 shows the number of years a country (column) first-order dominates another country (row).

For all years, (i) Belgium dominates Spain, Finland, France and the UK and (ii) Germany dominates Spain and Finland. Spain is stochastically dominated by each other country in at least four of the eight years, again illustrating the low competitiveness of Spanish firms. In sum, both Figure 3 and Table 4 show persistent and significant differences in competitiveness between the seven selected EU15 countries.

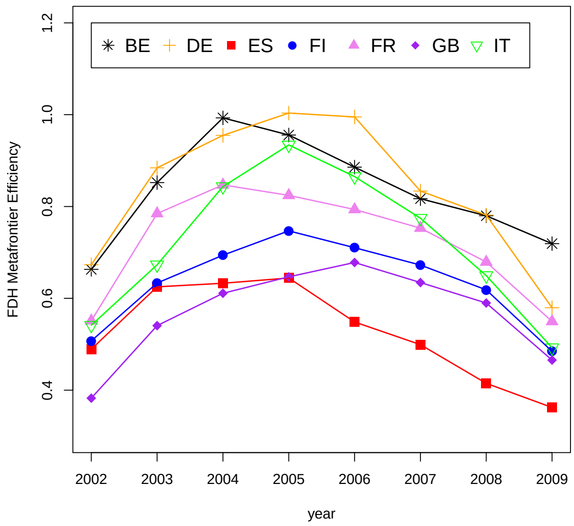


Figure 3: Median metafrontier efficiency

	BE	DE	ES	FI	FR	GB	IT
BE	0	0	0	0	0	0	0
DE	2	0	0	0	0	0	0
ES	8	8	0	4	8	4	4
FI	8	8	0	0	7	0	0
FR	8	5	0	0	0	0	0
GB	8	6	1	2	5	0	0
IT	3	1	0	0	1	0	0

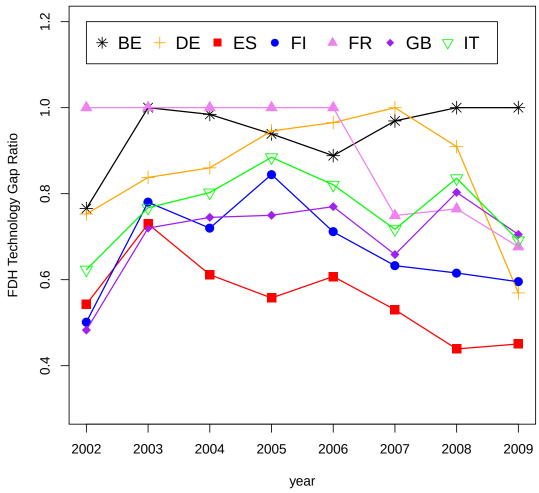
Table 4: Stochastic Dominance

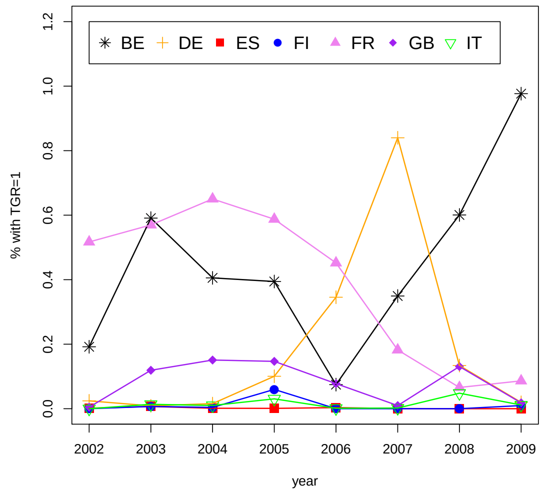
The technology gap ratio, defined as the ratio of metafrontier efficiency to technical efficiency ($TGR = ME/TE$), gives insight into technological differences. As discussed, a TGR equal to one indicates that there is no technology gap between the country and the metatechnology for the firm in question. Figure 4 shows respectively the weighted median

[24]However, it is not possible to reject non-dominance in favor of dominance over the whole support of the distribution (i.e., not possible at the boundaries). Therefore, as in Davidson and Duclos (2012), we test whether we can reject non-dominance over restricted ranges of metafrontier efficiency. In particular, we restrict the range of metafrontier efficiency studied between the 5 and 95 percentile.

TGR (left) and the % of observations with TGR equal to one(right). Primarely France, Germany and Belgium have defined the metatechnology over the period 2002-2009. Belgium defined a substantial part of the metafrontier, and is in the crisis-years clearly the '*benchmark*'. Spain, in contrast, clearly does not define the metatechnology. Further, half of Spanish firms have in recent years a TGR lower than 0.5, indicating a wide technology gap. Figure 4 illustrates that, in the pre-crisis year 2007, half of the Spanish firms, could double revenues if they would work under metatechnology conditions and not be restricted by the country-specific technology (keeping technical efficiency constant). Differently put, the low result of Spain in terms of competitiveness finds its origin in both inefficiency and a technology gap.

Figure 4: Technology Gap Ratio, weighted median (left) and % firms with TGR=1 (right)





3.3.3 Competitiveness dynamics

Figure 5 and Table 5 show respectively the weighted median estimated TFP change and number of years in the period 2003-2009 a country (column) stochastically dominates another country (row) in terms of TFP change. In the pre-crisis period, the majority of firms increased TFP in all countries except of Spain, where TFP change is negative since

2004. No effects of convergence or divergence can be found in the pre-crisis period. In the crisis period, we find that in Belgium and Spain, TFP change remains rather stable, but TFP change is very negative in the other countries. Obviously, technical productivity did not decline as much, our TFP index, which is revenue-based, captures not only technical productivity, but also country-specific demand effects, effects of inventory changes and influences of labor hoarding, all occurring during the crisis.[25] It is thus unclear what the true productivity effects are in 2008-2009, as country-specific confounding effects of the crisis significantly bias TFP estimation. Table 5 nicely illustrates the absence of convergence between countries in terms of TFP. No country dominates another country in terms of TFP growth more than three of the seven years. A further finding against convergence is that the country that is most, but still not frequently, dominated by other countries is Spain, a low-achiever in terms of competitiveness.

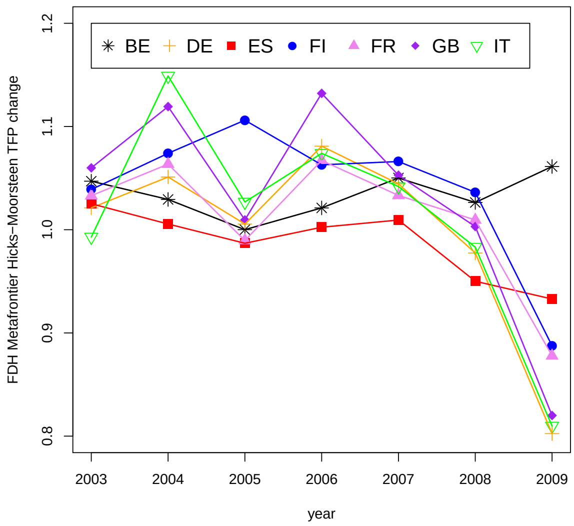


Figure 5: Median MHM TFP change

	BE	DE	ES	FI	FR	GB	IT
BE	0	0	0	1	0	0	0
DE	1	0	1	1	1	1	1
ES	2	0	0	3	1	3	3
FI	1	0	1	0	0	0	0
FR	0	0	0	1	0	0	0
GB	1	0	0	1	0	0	0
IT	1	0	1	2	0	0	0

Table 5: Stochastic Dominance

[25]We could include inventories into the output, but correct valuation of inventories can be problematic. Therefore, we focused on revenue, as in standard work in the firm-level TFP literature (e.g. Olley and Pakes (1996)).

3.3.4 Sensitivity analysis

To study the robustness of our findings, first, we studied the median figures and performed stochastic dominance tests i) with equal weighting of firms in stead of weighting by value added, ii) for the subsample of firms with 20 employees or more, iii) with equal weighting and for the subsample for firms with 20 employees or more. Results available upon request show that the findings are robust for altering the empirical strategy in these directions. Further, an analysis of the representativeness of AMADEUS data and firm size groups in Appendix B indicates that differences in size distributions between countries do not explain the differences in metafrontier efficiency and TFP growth.

Second, we test for the Belgian firms (for which we have access to confidential export figures via the National Bank of Belgium) whether the semiparametric estimates provide results that are in line with a stylized fact in the international trade literature: exporting firms are overall more competitive. Results in Appendix C illustrate that, overall, median figures pinpoint that exporters are more competitive than non-exporting firms (without making causality statements). To obtain additional insight, we refine the export status as follows: i) the firm exports only to EU15 countries, ii) the firm exports only to EU8 counties, iii) the firm exports also to non-EU28 countries. This refinement of export status has as disadvantage that for some sectors, results are flawed by outliers that are caused by the limited sample size in some categories of exporters. However, overall, we find that firms that also export to non-EU28 countries are more competitive than other exporting firms, again without making causality statements. While there is evidence for stochastic dominance over large segments of the distribution, exporting firms do not stochastically dominate non-exporting firm over the entire distribution (results available upon request). Median figures (and stochastic dominance tests available upon request) indicate no dominance in terms of TFP growth between exporting and non-exporting firms.

4 Firm-level efficiency growth and market share dynamics

4.1 Introduction

The efficiency (productivity) level of an industry is a weighted average of the technical efficiency of the firms that the industry is composed of. Firm-level data show that the assumption that industries are composed of identical and perfectly competitive firms is tenuous (e.g., Bailey et al., 1992; Bartelsman and Doms, 2000). Micro-level data permit to assess to what extent industry-level productivity growth can be explained by within-industry dynamics: firm-level productivity growth, reallocation of market shares between existing firms (incumbents) and entry and exit. If the efficiency of firms within a given industry differs substantially, industry-level productivity may change due to changes in the market shares of firms, even when the productivity of individual firms does not change. Decomposing industry-level productivity growth using firm-level data provides some insight into effects of within-industry dynamics that cannot be revealed through industry-level or country-level data. Melitz and Trefler (2012) point out gains from international trade in models that account for firm heterogeneity that consist in foreign competition raising industry-level productivity due to within-industry reallocation of market shares towards the most efficient firms. Recent (Schumpeterian) growth models stress the role of firm dynamics and reallocation of resources among incumbents and entrants (see review by Aghion et al., 2013). Bartelsman and Wolf (2013) find that forecasts of macro-level productivity growth based on computed micro-level components (firm-level growth and within-industry reallocation) outperform forecasts based on more aggregate data. Hyytinen and Maliranta (2013) discern a growing awareness among policy-makers that long-term competitiveness and growth may be hampered by inadequate within-industry dynamics.

Baily et al. (1992) find strong movement of US firms up as well as down the productivity distribution. Not all entrants have high productivity levels and not all firms that exit have low productivity before exit. In their analysis, entry and exit appear to be of only minor importance for productivity growth. A large part of industry-level productivity growth is explained by reallocation, in effect increases (decreases) in the output shares of high-productivity (low-productivity) plants. Haltiwanger (1997) finds that reallocation occurs in terms of productivity growth, as firms with positive (negative) productivity growth gain (lose) market shares. Olley and Pakes (1996) show that - in the US telecommunications equipment industry- reallocation of capital towards more efficient firms is more important for industry-level productivity growth, than firm-level productivity growth.

According to Foster et al. (2001), results of decomposition analysis vary considerably due to business cycle and industry-specific effects and differences in the methods used to decompose productivity growth. Conclusions on the role of firm entry and exit depend on the horizon over which changes are considered. A decomposition of TFP growth in four-digit US manufacturing industries, over the period 1977-1987, indicates that the within component (firm-level TFP growth) explains 50 up to 65% - depending on the method of decomposition - and net entry another 25% of industry-level TFP growth. The sign of the reallocation component is negative with the decomposition proposed by Baily et al. (1992) but positive when using the decomposition of Griliches and Regev (1995).

Scarpetta et al. (2002) report results of a decomposition of labor productivity for a group of ten OECD countries covering the period 1987-1997. They conclude that firm-level productivity growth is a more important factor for industry-level productivity growth than reallocation. The exit of low productivity firms contributes positively to industry productivity in mature industries whereas in technologically dynamic industries entry also plays an important role. In line with previous findings (e.g. Dunne et al., 1988 and review by Caves, 1998) they find substantial failure rates for entrants. Differences between the US and the EU countries in the analysis are not important in terms of firm churning (i.e. combined rate of entry and exit) but US entrants are on average smaller, relative to industry average, and have a lower labor productivity than incumbents, compared to entrants in Europe. The growth performance of entrants is however more impressive in the US than in Europe. Econometric estimations suggest that strict product market regulation has a negative impact on TFP, the effect being more substantial the further away a country or industry is from the technology frontier. Strict regulation on entrepreneurial activity and high adjustment costs of labor appear to reduce entry although the authors point out that there is no straightforward link between firm dynamics and productivity performance.

Altomonte (2010) decomposes labor productivity growth for four EU countries between 2000 and 2008. In France and Italy, firms that witness positive (negative) productivity growth lose (gain) market shares. In the UK there is little evidence of substantial firm-level productivity growth whereas for Sweden all components of TFP growth are positive. Altomonte perceives a possible conflict between different policy aims, as creating jobs - in view of creating a more inclusive society - could have a negative impact on productivity growth if jobs are created in firms with low-productivity (growth). His results suggest that this applies to France and Italy.[26]

Melitz and Polanec (2012) argue that the decomposition of both Foster et al. (2001) and Griliches and Regev (1995) provide biased results due to an inappropriate benchmark productivity level for firms that enter or exit a given industry and the fixed weights (market shares) that are used to disentangle within-firm productivity growth from reallocation. They propose a dynamic extension of the decomposition by Olley and Pakes (1996). Using data on Slovenian manufacturing firms covering the period 1995-2000, Melitz and Polanec find that the decompositions of Foster et al. (2001) and Griliches and Regev (1995) substantially underestimate the contribution of incumbents. Hyytinen and Maliranta (2013) apply a decomposition - similar to Melitz and Polanec (2012)- to labor productivity growth in Finland but stress the importance to distinguish between incumbents in terms of firm age. In Finland, productivity growth of old incumbents is the most important source of industry-level productivity growth. As entrants generally have a relatively low productiv-

[26] Boulhol and Turner (2009) and Dew-Becker and Gordon (2012) report evidence of a trade-off between employment and productivity due to the integration of low-productivity workers, as targeted by labor market reforms.

ity level, their initial contribution is negative. The negative effect of entrants is gradually mitigated through market selection, exit and productivity growth which relates to the argument by Dunne et al. (1988) that the long-run impact of entry depends on post-entry growth and exit of entrants.

In this section we use the method of Melitz and Polanec to decompose the technical efficiency growth in two-digit NACE industries for the seven EU countries for which we obtain semiparametric estimates of metafrontier efficiency (see previous section). We also propose a decomposition that accounts for different dynamics according to the age of incumbents, following Hyytinen and Maliranta (2013), and consider the impact of the economic slowdown in 2009. In Appendix H, we compare results based on firm-level output deflated by industry-level price indices to results for which firm-specific indices were used to deflate output.

4.2 Decomposition

Melitz and Polanec (2012) propose the following dynamic extension to Olley and Pakes (1996) to decompose the growth in industry-level productivity[27]

$$\Delta\Phi \equiv \Delta\overline{\varphi}_s + \Delta cov_s + S_{E2}(\Phi_{E2} - \Phi_{S2}) + S_{X2}(\Phi_{S1} - \Phi_{X1}) \tag{14}$$

Industry-level productivity is the average productivity of the firms that industry is composed of, weighted by the firms' share in industry value added ($\Phi = \sum_i s_i\varphi_i$ with s_i the share of firm i in industry value added and φ_i firm i's productivity). The first component ($\Delta\overline{\varphi}_S$) denotes the unweighted average change in the productivity of incumbents between period 1 and period 2. Reallocation is reflected by the second component (Δcov_S), the covariance change between the market shares and productivity of incumbents. The third and fourth component capture the contribution of respectively firms that enter and firms that exit ($S_{E2}(S_{X1})$: Aggregate share of entrants (exiting firms); Φ_S, Φ_E, Φ_X: Aggregate

[27] The decomposition is actually an aggregation of industry-level productivity from components of firm-level shares and productivity.

productivity of incumbents, entering and exiting firms). Melitz and Polanec point out that the use of different reference productivity levels for different groups of firms (Φ_{S2} for firms that enter in period 2 and Φ_{S1} for firms that exit in period 2) differentiates their method from Foster et al. (2001) and Griliches and Regev (1995). Hyytinen and Maliranta (2013) also argue that previous decompositions exaggerate the contribution of entrants to industry-level productivity growth and use a similar decomposition as Melitz and Polanec (2012), following Vainiomäki (1999) and Diewert and Fox (2010).

4.2.1 Incumbents as an homogeneous group

Industry-level efficiency growth is decomposed following Melitz and Polanec (2012), using the semiparametric estimates of firm-level efficiency for seven EU countries, as discussed in the previous section. As the decomposition analysis requires productivity levels we use the estimates of metafrontier efficiency (ME) throughout this section, both for levels and growth measures (i.e., we do not use the Hicks-Moorsteen TFP change estimates). In AMADEUS, the year of incorporation of a firm is reported for most countries. The year of incorporation is not necessarily the year of actual entry as it may take some time before a firm actually starts its activities. In our analysis entry is defined as the year for which AMADEUS first reports a strictly positive number of employees, as long as the firm is not older than five years according to the year of incorporation. For the UK the year of incorporation is not provided for most firms and entry is defined, irrespective of its age, as the first year with strictly positive employment after previous years(s) without employment. The analysis covers the period 2002-2009. In AMADEUS the year of exit is not reported for most countries. Exit is therefore defined as the year for which employment is no longer reported, after having been reported in previous year(s), insofar the firm does not reappear in the following years of the period under consideration. Differences between countries in coverage, reporting requirements and sampling are likely to affect our analysis, especially regarding entry and exit for which - out of necessity- a second best definition is applied.

Table 6 shows the average number, over the period 2002-2009, of incumbents, entrants and exiting firms by industry for each of the seven countries. The high number of entrants and exiting firms relative to the number of incumbents, especially in Germany and the UK may be due to sampling issues that result in an overestimation of entry and exit and call for caution in the interpretation of the entry and exit components as these may not fully reflect the contribution of real entry and exit.

Table 6: Summary table

Average number of incumbents (2002-2009)							
nace2	BE	DE	ES	FI	FR	GB	IT
15	286	309	3740	148	1093	396	2084
17	99	88	988	23	269	141	1611
22	119	266	1980	212	569	421	1144
24	182	316	1100	39	363	426	1160
25	66	292	1270	122	443	283	1334
26	153	190	2213	72	333	153	1400
28	216	813	4882	519	1618	607	4751
29	156	798	1871	298	670	200	3888
31	55	266	403	71	196	263	1192
36	65	170	1914	135	311	432	1988
Average number of entrants (2002-2009)							
nace2	BE	DE	ES	FI	FR	GB	IT
15	6	37	119	10	78	48	141
17	2	10	29	2	10	15	99
22	3	35	72	11	22	55	75
24	4	30	23	3	12	48	43
25	1	36	32	6	20	39	61
26	2	22	70	3	11	19	94
28	6	112	227	36	68	77	500
29	2	86	61	22	26	34	237
31	1	26	15	5	9	34	82
36	1	19	81	7	21	54	178
Survive 2007	0,71	0,35	0,65	0,68	0,33	0,46	0,6
Survive 2009	0,39	0,28	0,42	0,4	0,25	0,32	0,4
Average number of exiting firms (2002-2009)							
nace2	BE	DE	ES	FI	FR	GB	IT
15	22	94	376	30	250	84	272
17	15	36	160	8	76	42	314
22	16	119	257	55	151	136	196
24	19	68	90	9	64	77	112
25	7	93	131	17	94	73	206
26	17	65	236	13	59	33	242
28	24	331	618	97	329	171	948
29	16	223	208	60	151	56	593
31	8	74	56	17	39	67	198
36	8	60	276	30	87	129	378

Note: the rows Survive 2007 and Survive 2009 show the share of entrants in 2003 that are still active in respectively 2007 and 2009.

In most industries entry and exit are highly correlated (e.g., Dunne et al., 1988; Hopenhayn 1992; Asplund and Nocke, 2006). Entrants have a high probability of early exit. Of the entrants considered by Scarpetta et al. (2002), 30 up to 40% do not survive the first two years and after seven years only 40 up to 50% are still active. The last two rows of the summary on the number of entrants in Table 6 show the survival rates in our sample for firms that entered in 2003. In all countries, more than 25% of the 2003 entry cohort was no longer active in 2007.[28] By 2009 the survival rate dropped dramatically, undoubtedly explained by the recession.

Appendix D shows the detailed results by two-digit NACE industry, of a decomposition applied to each of the seven countries. Following Melitz and Polanec (2012), value added is used as the weight (market share) in the decomposition of industry-level efficiency growth. Table 7 summarizes the detailed results by reporting, for each country, the average over all industries and years of the relative contribution of each component to the growth in industry-level productivity. The relative contribution relates the components in absolute terms, as reported in Appendix D, to industry-level productivity growth in a given year. The median of the relative contributions is reported in brackets.

[28]The low rates for Germany and the UK are probably partly due to sampling issues as explained in the text and should be interpreted with caution.

Table 7: Average (median) relative contribution to industry-level efficiency growth

	Belgium	Finland	France	Germany	Italy	Spain	UK
Within-firm growth	1.23	0.16	1.47	1.8	-0.52	0.22	1.23
	(0.91)	(0.94)	(1.14)	(1.01)	(1.27)	(1.24)	(0.99)
Reallocation	0	0.66	-0.64	-0.97	1.2	0.76	0.05
	(0.10)	(0.04)	(-0.02)	(-0.01)	(-0.35)	(-0.27)	(-0.05)
Entry	-0.21	0.08	0.14	-0.04	0.06	0.02	-0.25
	(0.00)	(-0.01)	(0.03)	(0.00)	(0.02)	(0.01)	(0.02)
Exit	-0.03	0.1	0.03	0.22	0.26	0	-0.03
	(-0.00)	(0.00)	(0.02)	(0.02)	(-0.01)	(-0.01)	(0.05)

Note: The table shows the average (median in brackets), over all industries and years, of the four components as reported in Appendix D, relative to industry-level productivity growth.

Within-firm productivity growth contributes most to industry-level productivity growth in Belgium, France, Germany and the UK whereas for Finland, Italy and Spain reallocation is the most important component. On average, reallocation between firms appears to have a substantially negative impact on productivity growth in France and Germany suggesting that value added shifts towards less efficient incumbents. The negative reallocation component for France and Italy (median) is in line with the results reported by Altomonte (2010). Entering firms tend to decrease industry-level efficiency in Belgium and the UK and increase it in Finland and France. The interpretation of the entry component is not straightforward. Scarpetta et al. (2002) find that, on average, entrants in the US have a lower productivity relative to the productivity of incumbents than entrants in Europa. The impact of entrants on industry-level productivity in the US is therefore more negative than in Europe. Successful entrants however appear to witness more substantial growth in the US, relative to the EU, in the initial years after their entry. Exiting firms contribute to industry-level efficiency growth in Finland, Germany and Italy. The substantial differences between the average and median contributions, with in some cases even opposing signs, show that a small group of firms can explain the idiosyncratic pattern of industry-level dynamics. This may reflect the fact that industry dynamics, especially of young firms, is explained by a relatively small number of firms as Haltiwanger, Jarmin and Miranda (2013) find in their analysis of US job creation. OECD (2013), in a cross-country comparison of employment dynamics, find that only 5% of small start-ups (less than 10 employees and less than 3 years old) grow over four-year periods but they explain 24% of net job creation by their cohort. Especially in industries with a relatively low number of active firms, the entry, exit or productivity growth of a single firm can substantially affect industry-level productivity growth in a given year.

In Appendix E we discuss the transition matrices of metafrontier efficiency, constructed for the periods 2002-2005 and 2006-2009. The matrices show the probability of a firm to move up or down the metafrontier efficiency distribution over a given period. The relatively high shares on the diagonals of the matrices, i.e. the share of firms that remain in the same quartile, reveal the well-known persistence of efficiency (e.g, Bartelsman and Doms, 2000). However, as pointed out in the previous paragraph, a small group of young firms that do move up in the distribution can account for a disproportionate share of within-industry dynamics.

4.2.2 Incumbents grouped by age

Melitz and Polanec (2012) argue that previous decomposition analyses over-estimate (under-estimate) the contribution of entrants (incumbents) to industry-level productivity growth. The first two components in Table 7, which relate to incumbents, clearly dominate the contribution of entry and exit of firms. However, a cursory look at the data suggests that it may take some years before a new company operates at full efficiency. In Figure 6 the efficiency of entrants, starters, young firms and exiting firms (prior to exit) is shown, relative to the average efficiency of mature firms.[29] Table 8 provides the definition of the different groups of firms. Our age groups are similar to Haltiwanger et al. (2013) who

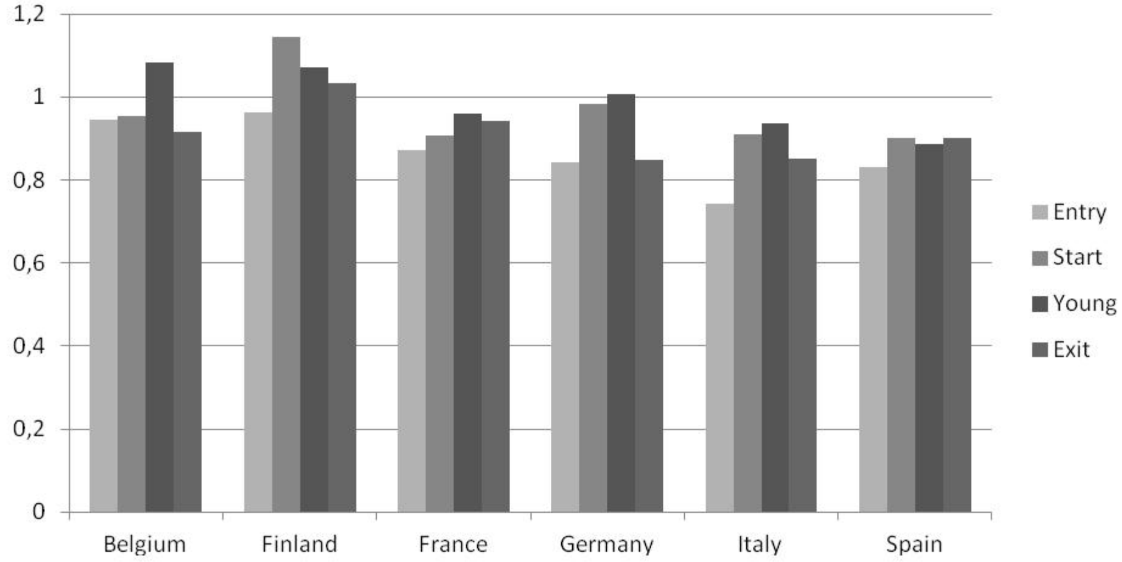
[29] See appendix A for industry-specific figures of the relative efficiency of the different firm groups.

stress the importance of young firms, defined as firms younger than 10 years and Hyytinen and Maliranta (2013) who perform a decomposition, similar to Melitz and Polanec (2012), to a sample of Finnish firms, with a breakdown of incumbents by age. In Figure 6, a ratio of 1 implies that the group of firms is, on average, as efficient as mature firms, a ratio smaller than 1 that the firms are on average less efficient. As data on the date of incorporation are only provided for a very small number of UK firms, the analysis is only done for six countries. On average, entering firms are less efficient than mature incumbents in all countries, in line with previous findings (e.g., Jensen et al. 2001; Scarpetta et al., 2002; Hyytinen and Maliranta, 2013).

Table 8: Definition of groups of firms

Entry	A firm is considered to enter in the first year for which employment is strictly positive in AMADEUS, provided that the firm is not older than 5 (based on its year of incorporation).
Exit	A firm is considered to exit in the year for which employment is no longer reported or no longer strictly positive after previous year(s) with strictly positive employment insofar that the firm does not reappear (re-entry) in one of the following years of the period 2002-2009.
Incumbents	
Starting	Firms younger than 5, excluding the year of entry
Young	Firms older than five and not older than 10
Old	Firms older than 10

Figure 6: Average efficiency relative to the efficiency of mature firms

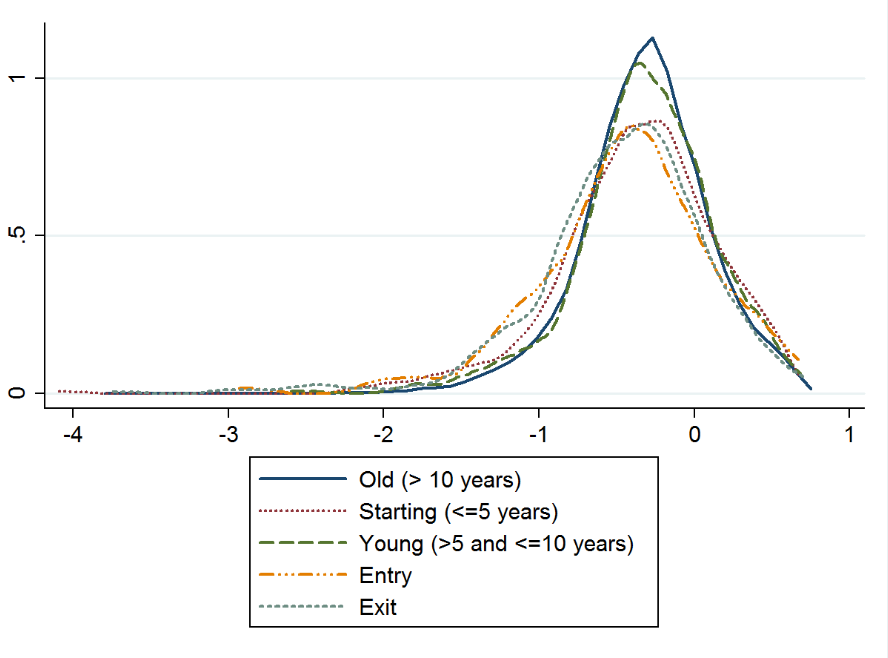


Note: The figure shows, for each group of firms, the average efficiency relative to the efficiency of mature firms, computed by two-digit NACE industry. Starting firms are up to 5 years old (considered after their year of entry) and young firms are between 6 and 10 years old.

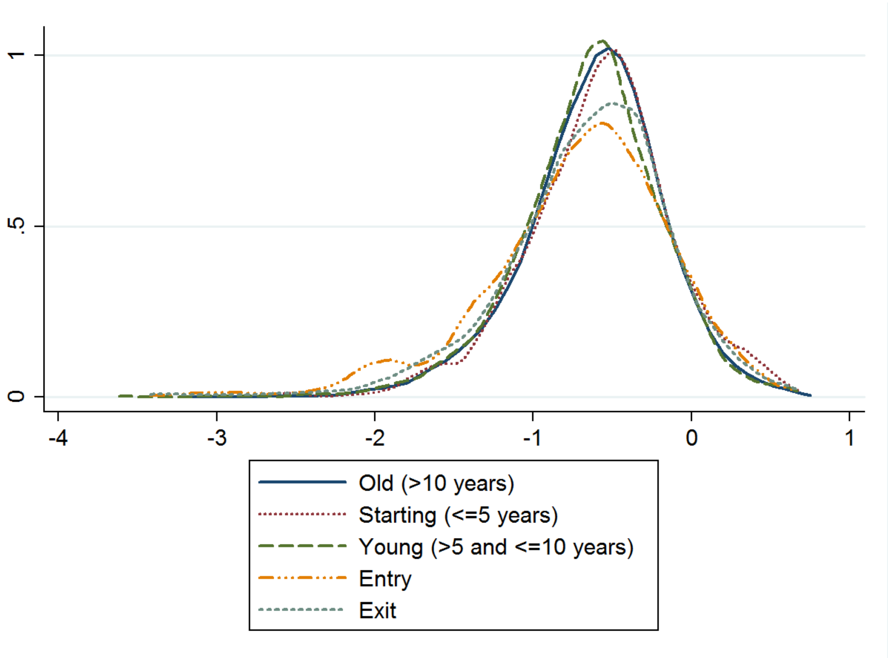
In all six countries, starting firms are more efficient than entrants. Except for Belgium and France, the bounce in efficiency after the year of entry is substantial. In Finland starting firms are even more efficient than mature firms. Efficiency further increases with age - except in Finland - especially in Belgium where young firms are more efficient than firms older than 10 years. In Italy and Spain, firms do not seem to catch up with older competitors even within a period of 10 years after entry. The difference in efficiency between entrants and young firms can to some extent be explained by market selection, in effect, entrants with low efficiency that exit within a short period after entry. Unreported computations show that the average productivity of entrants that survive at least three years is higher than the overall efficiency of entrants, suggesting that high productivity at the time of entry increases the probability of survival. However, this effect does not fully explain the difference between entrants and firms in the first years after their entry, which indicates that firms indeed need time to reach their optimal efficiency level. In

Finland, France and Spain exiting firms are on average more productive than firms in their year of entry. The average productivity of different groups of firms may blur differences in the distribution within those groups. This is revealed in Figure 7 and 8, in which the entire productivity distribution (kernel density) of the different groups is mapped for four countries. Whereas in Italy and Spain the productivity distribution of mature firms dominates the distribution of all other groups of firms over the entire range, in Belgium and Finland the end of the right tail of the distribution of entering and starting firms lies to the right of the end of the right tail of the distribution of mature firms. In these countries, a relatively small group of entrants and start-ups reaches a high level of efficiency from an early stage of their activities. In Finland the distribution of entrants and starters is close to the distribution of mature firms. After five years of activities, Finnish firms lose a part of their competitive edge as indicated by the right tail of young firms that lies to the left of the right tail of starting firms, which closely fits the right tail of mature Finnish firms. It apparently takes more time for a larger group of Belgian starters to catch up with the efficiency level of older firms than in Finland. In Italy and Spain the right tails of the distribution of entrants, starters and young firms are pretty tied but clearly dominated by the right tail of mature firms, again confirming that in these countries firms fail to increase their productivity to the level of older competitors, even 10 years after entry.

Figure 7: Productivity distribution of three age groups, entering and exiting firms - Part I

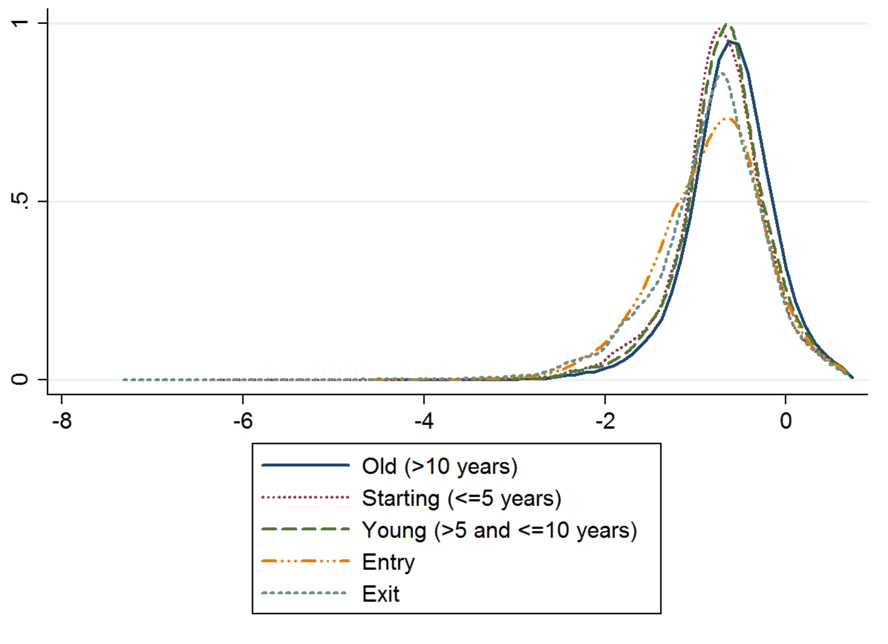


(a) Belgium

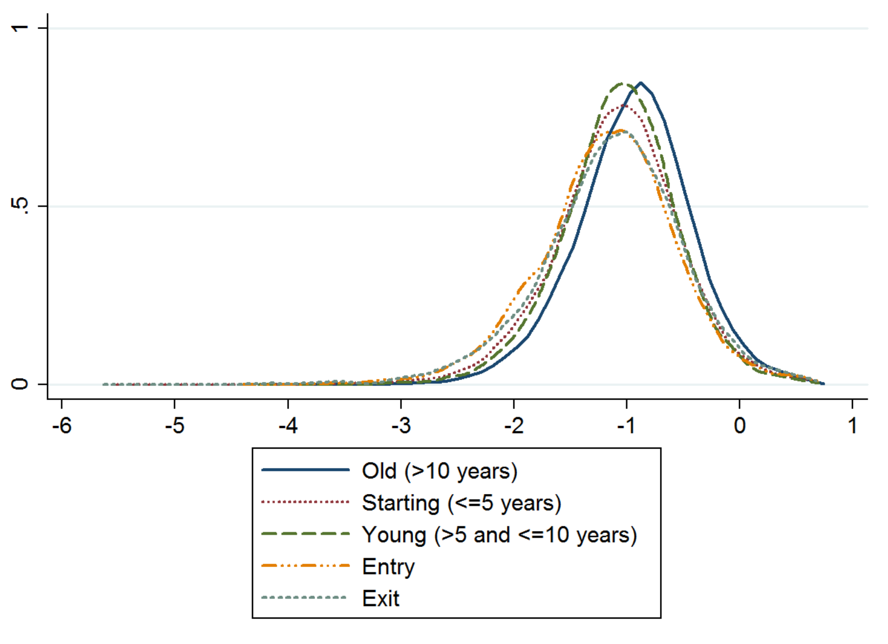


(b) Finland

Figure 8: Productivity distribution of three age groups, entering and exiting firms - Part II



(a) Italy



(b) Spain

Note: The Figure shows, for each group of firms, the kernel density function of productivity (relative to industry average) for the period 2002-2007 (excluding the years of global financial crisis and economic slowdown). The figures are produced with the kdensity function in STATA.

In Italy and Spain the left tail of the distribution is also substantially longer than in Belgium and Finland.

The stepwise increase in average productivity upon entry of firms, as apparent in Figure 6, 7 and 8, corroborates previous theoretical and empirical contributions that stress the importance of learning and experience. Jovanovic (1982) proposes a theory of "noisy" selection in which potential entrants do not know their efficiency before they actually enter an industry. After entry they gradually learn about their true level of efficiency. New firms that find out that their costs are too high to be profitable will exit. The model can explain why new firms grow faster than older firms but also why they have a lower probability to survive, as supported by empirical evidence on the up-or-out pattern of start-ups (e.g., Dunne et al., 1988; Wagner, 1994; Haltiwanger et al., 2013; OECD, 2013). Caves (1998) distinguishes models of passive learning (e.g., Jovanovic, 1982; Hopenhayn, 1992; Cabral, 1993) from models of active learning (e.g., Pakes and Ericson, 1998). He points out that both views are not mutually exclusive and that the preponderance of one of the mechanisms may be industry-specific. In the model of Agarwal and Gort (1996) technical efficiency of young firms relative to more mature incumbents depends on the trade-off between skills formation, which increases with experience (firm age), and the increased inability of firms to adapt their initial endowments (technology) to changes in the market or technology. Learning by doing may take some time but in high-tech industries entrants appear to have an advantage over mature firms. Entry, exit and survival of firms depend on the development stage of product cycles. The empirical evidence put forward by Bahk and Gort (1993) indicates the importance of plant-specific learning in US manufacturing industries. Organizational learning appears to continue for over 10 years and capital learning for 5 to 6 years after entry. Analysis of within-industry employment growth reveals strong dynamics in the group of entrants for at least 10 years after entry (Foster et al,. 2013b; Haltiwanger et al., 2013; OECD, 2013).

By only considering entrants as new firms in the first year of their activities, the contribution of start-ups to industry productivity growth may be under-estimated. Rather than considering all incumbents as a single group we reapply the analysis proposed by Melitz and Polanec (2012) by splitting up incumbents into the three age groups as defined in Table 8. The decomposition of industry-level productivity growth with a breakdown of incumbents by age follows the following extension of equation (1):

$$
\begin{aligned}
\Delta\Phi \equiv\ & \Delta\overline{\varphi}_{s,Mature} + \Delta cov_{S,Mature} \\
& + \Delta\overline{\varphi}_{s,Start} + \Delta cov_{S,Start} \\
& + \Delta\overline{\varphi}_{s,Young} + \Delta cov_{S,Young} \\
& + S_{E2}(\Phi_{E2} - \Phi_{S2}) + S_{X2}(\Phi_{S1} - \Phi_{X1})
\end{aligned} \tag{15}
$$

In Table 9, the average share, over all industries and years, of each of the three age groups in the total number of incumbents is reported. On average, more than 70% of incumbents are older than 10 years in all six countries.

Table 9: Summary table: average share of each age group in the number of incumbents

	Start	Young	Mature
BE	0,04	0,08	0,88
DE	0,13	0,14	0,73
ES	0,08	0,16	0,76
FI	0,11	0,13	0,76
FR	0,08	0,11	0,81
IT	0,10	0,13	0,77

The share of starting firms is the highest in Germany and rather low in Belgium whereas the share of young firms appears to be the highest in Spain. Asplund and Nocke (2006) find that the share of young firms is higher in large markets or markets with high fixed production costs.

Table 10 reports the results of a decomposition analysis with incumbents split up into three age groups, following formula (2). The average, over years and industries, of the relative contribution of each component is reported. Appendix F shows the results by two-digit industry.

Table 10: Average (median) relative contribution to industry-level efficiency growth

	Belgium	Finland	France	Germany	Italy	Spain	Correlation Productivity growth
Within-firm growth	0.76	0.51	1.18	1.45	0.87	1.11	0.04
(Mature)	(0.89)	(1.01)	(1.15)	(1.05)	(1.30)	(1.28)	(-0.54)
Reallocation	-0.16	0.25	0.04	-0.31	0.04	-0.43	0.43
(Mature)	(0.08)	(0.02)	(-0.15)	(-0.03)	(-0.26)	(-0.35)	(0.63)
Within-firm growth	-3.33	-1.01	1.85	0.92	1.16	-3.25	0.51
(Start)	(0.45)	(0.76)	(0.95)	(1.08)	(1.39)	(-1.74)	(0.81)
Reallocation	0.09	-0.21	-0.08	0.02	0.06	1.94	-0.86
(Start)	(0.00)	(0.00)	(-0.01)	(0.04)	(-0.01)	(0.13)	(-0.84)
Within-firm growth	3.59	0.56	0.88	1.21	0.85	-10.32	0.92
(Young)	(0.99)	(0.69)	(1.30)	(0.89)	(1.38)	(-4.97)	(0.90)
Reallocation	0.08	0.21	-0.09	-0.04	-0.04	-0.08	0.09
(Young)	(-0.01)	(0.04)	(-0.01)	(-0.03)	(-0.04)	(-0.03)	(0.09)
Entry	-0.04	0.09	0.09	-0.03	0.05	0.02	-0.03
	(0.00)	(0.00)	(0.03)	(0.00)	(0.02)	(0.01)	(0.10)
Exit	0.00	0.04	0.02	0.01	0.01	0.02	-0.44
	(0.00)	(0.00)	(0.02)	(0.02)	(-0.01)	(-0.01)	(0.66)

Note: The table shows the average, over all industries and years, of the relative components of a decomposition in which incumbents are divided into three groups: starting (after entry but younger than 5 years); young (between 6 and 10 years old) and mature (more than 10 years old). To reduce the bias due to a small number of extreme values, the minimum and maximum observation for each country, are not considered in computing the average. As an alternative, the median of the relative components is reported in brackets.

The last column shows the cross-country correlation between the average (median) relative components and industry-level productivity growth.

The reallocation component for each age group of incumbents shows the extent to which market shares, within the entire group of incumbents, shift towards efficient firms in a specific age group of incumbents. The last column shows the cross-country correlation between the average relative contribution of a given component and average industry-level productivity growth. The simple average is substantially affected by a small number of "extreme" values. This may reflect the strong impact of a small group of young firms on industry dynamics, as mentioned before. As can be seen in Figure 7, in Belgium and Finland a small group of entrants, start-ups and young firms appears to be more efficient than the most efficient mature firms. Despite their small number, these highly efficient firms may have a strong impact on industry-level productivity growth. As can be seen in Appendix F, some large contributions of components appear in industries with a low number of firms, e.g. NACE 31 and NACE 36 in Belgium. Given the low number of firms the performance of individual firms will have a strong relative impact on industry performance. However, the efficiency estimates are less reliable for industries with a small number of firms. The "extreme" values may therefore also result from measurement issues. To reduce this potential bias we compute the average relative contribution of each component leaving out the minimum and maximum observation for each country. As an alternative robustness check we also report, in brackets, the median of all relative components. As in table 7, the contributions of incumbents dominate the impact of entry and exit but a substantial part is explained by starting and young firms. Productivity growth of starting firms contributes more to industry-level productivity growth than productivity growth of mature firms in France and Italy and its contribution is also substantial in Germany whereas it is negative in Belgium, Finland and Spain. Reallocation towards efficient starting firms has a strong positive impact on industry-level productivity growth in Spain. Except for Spain, the contribution of productivity growth of young firms is positive in all countries and especially important in Belgium. Reallocation of market shares (of all incumbents) towards efficient young firms contributes positively to industry-level productivity growth in Belgium and Finland but, in contrast with reallocation between starting firms, the impact of reallocation towards young firms is negative in four out of the six EU countries. The negative reallocation component of starting firms in Finland is in line with the results reported by Hyytinen and Maliranta (2013) who find that a large share of young Finnish firms that witness strong growth have relatively low productivity. They also find that firm-level growth is the most important component of industry-level productivity growth and that the exit of young firms with low productivity contributes positively to industry-level performance. The positive entry component and the larger within component for young Finnish firms than for incumbents in Table 10 are in contrast with the results of Hyytinen and Maliranta (2013). This may be explained by the fact that they consider labor productivity whereas we consider metafrontier efficiency, which is closer to a TFP measure. Scarpetta et al. (2002) find that a decomposition of TFP provides different results than a decomposition of labor productivity. The reallocation component is more substantial when considering TFP and net entry strongly contributes to productivity growth in terms of TFP, explained by the entry of firms with high TFP. Comparing the results based on TFP to results based on labor productivity they tentatively conclude that mature incumbents appear to raise labor productivity by substituting capital for labor whereas new firms enter with the right mix of new technologies and labor, resulting in high TFP but not necessarily high labor productivity.

The results of the decomposition by two-digit industry, as reported in Appendix F, are generally in line with the relative contribution of the different components across all industries, e.g. the positive contribution of productivity growth of young firms in most industries. However, industry-specific effects are apparent. For example, the strong overall negative contribution of productivity growth of young firms in Spain is found in NACE 17; NACE 22, NACE 24 and NACE 25 but in NACE 26 (non-metallic mineral products) and NACE 28 (fabricated metal products, except machinery and equipment) the contribution of this component to industry-level productivity growth is actually highly positive.

The last column in Table 10 shows the strong positive cross-country correlation between the relative contribution of the productivity growth of starting and young firms and industry-level productivity growth of countries. The shift in market shares towards starting firms, which as mentioned before is especially strong in Spain, is negatively correlated with average efficiency growth. Rather than productivity growth of mature firms it appears to be reallocation towards the more efficient mature firms that explains country differences in average industry-level productivity growth. The averages in Table 10 and the median, reported in brackets, generally provide a similar pattern but also reveal substantial differences, with the sign of the relative contribution of some components even changing signs. The most robust finding is the strong link between the contribution of productivity growth of young firms and industry-level productivity growth.

Table 11 shows the average contribution of the different components (relative to industry-level productivity growth), computed by relating each relative component to the cross-country average for each year and industry.

Table 11: Average (median) contribution (relative to cross-country average)

	Belgium	Finland	France	Germany	Italy	Spain	Correlation Productivity growth
Within-firm growth	-0.19	0	-1.15	0.52	0.87	0.11	-0.39
(Mature)	(-0.04)	(-0.08)	(0.06)	(0.05)	(0.03)	(-0.02)	(0.33)
Reallocation	1.84	1.62	-0.38	0.11	-0.44	-2.53	0.66
(Mature)	(0.29)	(0.51)	(-0.53)	(-0.14)	(-0.04)	(-0.28)	(0.02)
Within-firm growth	-0.89	0.15	1.35	0.9	1.76	-2.85	0.71
(Start)	(0.43)	(0.12)	(0.77)	(0.77)	(0.91)	(-1.56)	(0.89)
Reallocation	0.15	-0.15	-0.08	0.16	-0.13	0.03	0.09
(Start)	(0.07)	(0.08)	(-0.46)	(0.32)	(-0.13)	(0.50)	(-0.73)
Within-firm growth	2.99	2.52	3.86	1.56	1.72	-12.54	0.93
(Young)	(1.10)	(0.96)	(1.01)	(0.99)	(1.05)	(-5.21)	(0.89)
Reallocation	5.51	4.02	-0.24	-7.1	-1.49	0.2	0.01
(Young)	(0.00)	(0.97)	(-0.32)	(-0.41)	(-0.23)	(-0.28)	(-0.06)
Entry	-0.53	-0.68	0.61	-1.07	0.9	0.24	-0.1
	(-0.58)	(0.30)	(0.13)	(-0.81)	(0.34)	(0.14)	(-0.36)
Exit	0.97	1.15	-1.16	0.42	-0.81	-1.31	0.33
	(0.51)	(0.33)	(0.11)	(0.25)	(-0.44)	(-0.15)	(0.45)

Note: The table shows the average, over all industries and years, of the relative components of a decomposition in which incumbents are divided into three age groups as defined in Table 8, relative to the cross-country average for that component. To reduce the bias due to a small number of extreme values, the minimum and maximum observation for each country, are not considered in computing the average. As an alternative, the median of the relative components is reported in brackets. The last column shows the cross-country correlation between the average (median) relative components and industry-level productivity growth.

A negative term for a given country in Table 11 does not necessarily imply a negative relative contribution of the component as it may indicate that the contribution is positive but less substantial in that country than the cross-country average for that industry in a given year. Table 11 may be more informative to explain cross-country differences in average productivity growth, as revealed by the correlations reported in the last column.

Efficiency growth of young firms now clearly dominates all other components, with the impact being positive in all countries except for Spain. The cross-country correlation of this component with average productivity growth is again positive and extremely high (0.93). The correlation of the productivity growth component of starting firms is also positive and substantially higher than in Table 10 whereas the correlation of the reallocation component of starting firms is no longer negative. The correlation of the productivity growth component of mature firms is negative whereas the higher positive correlation of the reallocation component for mature firms confirms the importance of reallocation of market shares towards more efficient mature incumbents.
Comparing the averages in Table 11 to the medians, reported in brackets, again reveals the robust positive link between productivity growth of young firms and industry-level productivity growth.
To assess the statistical significance of the impact of firm-level efficiency growth and reallocation, we regress annual industry-level efficiency growth for each individual industry and country on the relative contributions of the components reported in Table 10. To account for cross-country and cross-industry differences in efficiency growth and potential cyclical effects (see section 4.2.3) we include country, industry and year dummies in the regression. The estimates for the components are reported in Table 12. The only relative contribution of a component that appears to be linked to industry-level efficiency growth in a statistically significant way is the positive impact of efficiency growth of young firms, in line with the high correlation for this component in Tables 10 and 11. There are no statistically significant country effects and only the positive coefficient of the industry dummy for manufacture of electrical machinery and apparatus n.e.c. (NACE 31) is statistically significant. The coefficients of the year dummies are positive and significant for 2004 and 2005, reflecting a strong pro-cyclical effect for these years of high economic growth. The coefficient for 2008 and 2009 is negative but not statistically significant. This may be explained by some of the counter-cyclical effects that we find for 2009 in section 4.2.3. The fact that no country dummy is statistically significant may strike as somewhat surprising but seems to support the finding in the previous section that there are no clear indications

of convergence in efficiency levels between countries.

Table 12: Regression of industry-level efficiency growth on relative contributions

Dependent: industry-level productivity growth	**Coefficient (-t-value)**
Within-firm growth (Mature)	-0.0013 (-0.66)
Reallocation (Mature)	-0.0009 (-0.36)
Within-firm growth (Start)	-0.0001 (-0.22)
Reallocation (Start)	0.0005 (0.76)
Within-firm growth (Young)	0.0004 (1.95)*
Reallocation (Young)	-0.0035 (-0.50)
Entry	0.0040 (0.19)
Exit	0.0037 (0.57)
Adj. R-squared: 0.07	
F(28, 391): 2.14**	

Note: The table shows the results of a regression of annual industry-level productivity growth in each individual industry and country, on the relative contributions of the components, as reported in Table 10. Country, industry and year dummies are included in the regression but not reported for reasons of clarity. *, ** denotes statistical significance at 5%, 1%.

The results reported in Tables 10 and 11 show that considering incumbents as a single group conflates diverging contributions to industry-level productivity growth, of different age groups. They are in line with Barba Navaretti et al. (2012) who, using data from the EFIGE survey on a sample of French, Italian and Spanish firms covering the period 2001-2008, find that controlling for country and industry effects as well as firm-specific characteristics (e.g., qualification of labor force and involvement in R&D activities), the age of firms is a significant explanatory variable of firm-level growth. Fort et al. (2013) also stress the essential distinction between firm size and firm age. Whereas young firms are, by and large, small firms, in many industries small older firms are prevalent (See Appendix G for a discussion on the link between firm age and size). An analysis of employment dynamics in 17 OECD countries shows that young firms create a disproportionate number of jobs (OECD, 2013). Hyytinen and Maliranta (2013) pointed out that the positive impact of entry only comes with a lag. As entrants are, on average, less efficient than incumbents, the direct impact of entry on industry-level technical efficiency is generally negative. Only after market selection (exit of less efficient firms) and productivity growth due to learning and experience do start-ups contribute positively to industry performance.

Haltiwanger, Jarmin and Miranda (2013) find that the negative correlation between employment growth and size disappears when the age of firms is controlled for. They point out the importance of theoretical models as well as empirical analysis that focus on start-ups that accounts for the fact that the growth dynamics of start-ups and young firms differs from that of more mature firms.

Our results also seem to corroborate the view of, among others, Dunne et al. (1988); Wagner (1994); Bartelsman et al. (2004) and Bravo-Biosca (2010) that the growth of firms after entry is more important than entry rates.[30]

4.2.3 Business cycles and the Great Recession

In his seminal contribution, Solow (1957) acknowledges that if the utilization rate of capital is not fully accounted for, measurement of productivity growth will be biased. This bias can explain the well-known pro-cyclical pattern of most TFP measures (e.g., Hall, 1991; Klette and Griliches, 1996; Basu et al., 2006; Tipper and Warmke, 2012; Planas et al., 2013). Basu et al. (2006) distinguish the cyclicality in aggregate TFP due to non-technological

[30]Conclusions on the effects of entry and exit based on AMADEUS are moreover less reliable due to problems to identify real entry and exit.

effects (e.g., differences in utilization of inputs over the business cycle) and due to actual improvements in technology. Whereas unobserved differences in utilization of capital and labor result in a pro-cyclical bias of TFP growth estimates, according to the authors the short-run impact of technological progress reduces factor utilization, which if not fully accounted for results in the underestimation of TFP growth. Technology improvements only appear to increase inputs, output and TFP with a delay of up to two years. Basu et al. (2006) argue that the pro-cyclical pattern found in most TFP estimates is explained by the pro-cyclical non-technology effects (especially factor utilization) which are substantial enough to outweigh the counter-cyclical impact of technological progress. Unobserved differences in the utilization of labor and capital over the business cycle will result in a pro-cyclical bias in firm-level productivity growth. In assessing the impact of business cycles on employment dynamics, Fort et al. (2013) find that young/small firms are more vulnerable to business cycle shocks than their more mature counterparts. They find that young (small) firms are more vulnerable to business cycle shocks than small mature firms which they explain by the limited reputation of young firms in product and credit markets. Young firms witness a sharper decline in sales in periods of credit market tightening. Economic slowdown reduces the positive difference in net job creation between young/small and large/mature firms. Businesses younger than 10 years account for 37% of the decline in net job creation in the US between 2006 and 2009, although they only account for 22% of employment. Mature/large firms are known to hoard labor to a far larger extent than young/small firms which are quicker to lay off workers during recessions and thereby account for a disproportionate part of the decline in job creation during recessions (Gertler and Gilchrist, 1994; Sharpe, 1994; Fort et al., 2013; Foster et al., 2013a). As changes in capacity utilization are not fully accounted for in the estimation of productivity this may explain why the pro-cyclical pattern of TFP estimates is more substantial for mature firms than for start-ups.

Other components of industry-level productivity growth are also known to be subject to business cycle effects. According to Caballero and Hammour (1994), the high rate of job destruction in recessions supports the view that recessions are periods of "cleansing" in

which mature firms with outdated technology and products are forced to exit as they can no longer produce profitably. In a similar vein, Solon et al. (1994) argue that, in recessions, firms will first lay off the less productive (skilled) workers. As a result, real wages (and productivity) may increase simply due to a composition effect.
The recent economic downturn, following the worldwide financial crisis in 2008 may, due to its severity and duration, differ from previous recessions in its impact on within-industry dynamics. Foster et al. (2013a) find that reallocation towards efficient establishments, which in normal times plays an important role in the US, slowed down substantially during the Great Recession (2007-2011) and the reallocation moreover enhanced productivity to a lesser extent than in previous recessions in the period 1981-2011. Petrosky-Nadeau (2013) finds that the strong and unusually counter-cyclical increase in aggregate TFP in the US following the financial crisis results more from job losses at surviving establishments (cleansing along the lines of Solon et al., 1994) than from job losses due to bankruptcy and exiting firms (cleansing along the lines of Caballero and Hammour, 1994). Lee and Mukoyama (2007) show that in the US, manufacturing plants that enter during booms are on average smaller and up to 20% less productive than plants than enter during recessions.[31] Differences between plants that exit during booms and plants that exit during recessions appear to be less substantial.

To assess the business cycle effect of the components of industry-level productivity growth we report, in Table 13, the difference between the relative contribution of firm-level growth, reallocation, entry and exit in 2009 and the average over the period 2003-2007.[32] Given the indications in previous studies of different business cycle effects according to age we consider the results of the decomposition in which incumbents are split into three age

[31] Clementi and Palazzo (2013) argue that a positive productivity shock increases the number of entrants but their average efficiency level will be lower. As a result output and TFP will be lower than without this selection mechanism. The higher entry rate has a permanent positive impact on long-run productivity as it increases the pool of young firms that can raise their efficiency and size over time.

[32] In 2009 all six considered EU countries witnessed substantial negative growth. In 2003 economic growth was low in Belgium, Germany, France and Italy but not in Spain and Finland.

groups.

The pro-cyclical pattern of TFP is reflected in the fact that firm-level efficiency growth is more negative in 2009 than in the period 2003-2007, at least for young and mature firms. For starting firms, the contribution of firm-level growth is actually more positive in 2009 in Belgium, Germany and Finland which may be explained, as in the US, by start-ups that lay off workers quicker than more mature firms. The decreased contribution of within-industry reallocation during the Great Recession, found by Foster et al. (2013a) appears to apply, in our data set of EU countries, to starting firms and less to older firms. Results indicate a substantial shift in market shares in 2009 towards more efficient mature firms, e.g. indications of a substantial "cleansing" effect of the Great Recession. The larger positive contribution of the entry component also corroborates the finding that entrants in the US are relatively more productive in periods of economic slowdown than during expansions, as shown by Lee and Mukoyama (2007) and Foster et al. (2013a). The larger positive contribution of the exit component in 2009 for all six countries indicates that the recent slowdown forced more low efficiency firms to exit than in the period of higher economic growth. This again seems to corroborate the argument of "cleansing" and is in line with results for recessions in the US except for the Great Recession when the positive contribution of exit diminished (Foster et al., 2013a: p. 22).

Table 13: Difference in relative contribution between 2009 and 2003-2007

	Belgium	Finland	France	Germany	Italy	Spain
Within-firm growth (Mature)	-0,04	-0,2	-1,09	-0,2	-0,06	-2,1
Reallocation (Mature)	0,38	0,51	0,38	0,1	0,33	1,94
Within-firm growth (Start)	5,87	1,52	-2,83	0,77	-6,46	-1,44
Reallocation (Start)	-0,08	-1,14	0,19	-0,02	-1,75	-0,08
Within-firm growth (Young)	-3,46	-0,92	-0,16	0,14	4,53	-4,21
Reallocation (Young)	-0,01	0,08	0,18	-0,09	0,09	0,15
Entry	0,02	0,02	0,38	0,05	-0,03	0,13
Exit	0,11	0,11	0,08	0,02	0,06	0,11

Note: The table shows the difference between the average relative contribution of different components of industry-level productivity growth between 2009 and the period 2003-2007.

The positive contribution of productivity growth of start-ups in 2009, probably explained by the lay-off of workers, reveals the more general trade-off that exists between employment growth and productivity growth as showed by Boulhol and Turner (2009) and Dew-Becker and Gordon (2012). The figures in Appendix G show the link between the annual growth rate in the number of employees and the annual productivity growth over the period 2002-2009. The negative link in all seven countries suggests that there is indeed a trade-off between employment and productivity. The link is also negative for all countries if we look at six-year period growth rates (levels in 2007 relative to levels in 2002).

5 Concluding remarks

In this paper, we analyze firm-level competitiveness in terms of productivity (technical efficiency), for seven EU15 countries. Existing firm-level empirical studies of TFP rely on parametric TFP approaches that relax exogeneity assumptions, but impose a priori a functional relationship between inputs and output, although economic theory hardly ever defines a specific functional form.

We contribute to this literature by advocating a semiparametric benchmarking alternative that directly deals with the potential function misspecification bias. No a priori assumptions are imposed on the functional form of the input-output relation. To deal with the noise that is present in any firm-level dataset, we relax the deterministic approach of the traditional nonparametric frontier estimations, by using a semiparametric stochastic frontier-based metafrontier methodology. From the country-specific sectoral frontiers, a sectoral stochastic metafrontier is estimated that envelops the country-specific frontiers and which constitutes as such the benchmark to assess firms' efficiency. The production frontiers are obtained in two steps: first, pre-withening the data from noise using local linear maximum likelihood estimation and second, estimation of the global frontier from free disposable hull. We determine the level of competitiveness by analyzing metafrontier efficiency and the technology gap and indicate the competitiveness dynamics by studying Hicks-Moorsteen metafrontier TFP change.

For the competitiveness analysis, we use firm-level information from the AMADEUS dataset of Bureau van Dijk in augmented form, i.e. compiling into one database the information provided in each issue of AMADEUS, keeping for each year within the time range the last available information. In this way, we keep the availability over time as consistent as possible: each firm is included in the database with the longest possible time series of data. To obtain reliable sector frontier estimates at the national level, we impose a lower bound on data availability of 50 observations by sector and year annually. Based on this criterion, we are able to analyze firm-level efficiency in 10 NACE 2-digit sectors for a set of seven EU15 countries for the period 2002-2009. The resulting sample contains comparable production information for 620,342 observations of 140,595 firms.

Given firm heterogeneity, we use stochastic dominance tests of the country-specific cumulative distributions of metafrontier efficiency, the technology gap and productivity growth to characterize competitiveness. Summarizing a pattern that seems common to all the sectors considered, in general Belgium and Germany (followed by France) constitute the benchmark countries as regards metafrontier efficiency and technology gap, whereas Spain lags behind in terms of competitiveness both in terms of efficiency and technology. As regards TFP-growth, the cumulative distribution of any country seems neither to dominate nor to be dominated. Hence, while our results show wide and persistent differences in efficiency levels within the EU15, productivity growth seems rather homogeneous between countries. From this we can infer the absence of convergence in efficiency between EU countries.

Analysis of firm-level productivity growth and market share dynamics provides some insight on industry dynamics that is beyond the scope of more aggregate data. If productivity levels of firms within the same industry differ, as micro-level data clearly bear out, industry-level productivity may change due to the reallocation of market shares (including entry and exit), even without any change in the technical efficiency of firms. Melitz and Polanec (2012) argue that previous decomposition analyses over-estimate the impact of entry and exit on industry-level productivity growth. Following their method, our decomposition using semiparametric estimates of technical efficiency for seven EU countries, confirms that firm-level productivity growth and reallocation between incumbents is the main driver of industry-level productivity. However, our analysis also shows the need to differentiate incumbents by age. It takes time for new firms to raise their technical efficiency. Firms are generally less efficient than existing competitors in the year of entry but their efficiency gradually increases with experience, at least for those entrants that survive. In Finland, firms younger than five years are on average more efficient than other (older) competitors. In Belgium and Germany it takes more time for new firms to become efficient. In Italy and especially in Spain newly created firms seem unable, even within a period of ten years after entry, to catch up with older firms. In line with previous studies on firm dynamics, our results indicate that post-entry growth - more than entry and exit as such - explains cross-country differences in industry-level growth and warrant further examination into (institutional) factors that affect post-entry growth. Whereas productivity growth of starting and young firms is the main driver of industry-level productivity, for older firms reallocation towards more efficient incumbents is more important than further productivity growth, for which the potential is more limited than for younger competitors. If it takes time for new firms to raise their efficiency level, it apparently takes even more time for efficient firms to build a strong market position.

The impact of entry and exit appears to be rather limited although differences between countries in coverage of the firm-level data hamper proper identification of real entry and exit.
The importance of young firms is confirmed by a regression of industry-level productivity growth on the computed relative components. Controlling for country, industry and year effects the productivity growth of young firms is the only relative component for which the impact on industry-level productivity growth is statistically significant.

In 2009, the final year of the period that we consider, EU countries witnessed substantially negative growth. Previous empirical work provides evidence on business cycle effects in the components of industry-level productivity growth. Recent studies show that the slowdown after the financial crisis in 2008 may have been so severe and enduring as to have resulted in effects that differ from previous milder recessions. Comparing the relative contribution of the different components in 2009 to the average over the period 2003-2007 indicates the importance of age in assessing the business cycle effect. The well-known pro-cyclical effect due to differences in the utilization of capital and labor is found to have been substantial for mature firms whereas 2009 appears to have resulted in a positive impact on productivity growth of starting firms in Belgium, Finland and Germany. This result could be explained by the fact that young (small) firms are less reluctant than mature firms to lay off (high-skilled) workers in recessions. There are indications that "cleansing" - a shift in market shares towards more efficient firms - is more prevalent for mature firms in recessions than for start-ups. The relative contribution of the entry component for 2009 is more positive than in the period 2003-2007, in line with evidence for the US that in recessions entrants are on average more efficient than entrants in periods of high economic growth. The higher positive contribution of the exit component also seems to corroborate the "cleansing" effect. Recessions appear to force low productivity firms to exit to a larger extent than in booms.

The results of the decomposition of industry-level productivity growth for seven EU countries over the period 2003-2009 show that growth of start-ups after entry is a more critical factor than the actual entry rate. Just as firm-level data clearly bear out that the notion of a representative firm is tenuous at best, it also appears to be important to consider the entire distribution of productivity growth of starting and young firms. Whereas starting firms have a high probability to be forced to exit in an early stage, a small share of surviving start-ups explains a disproportionate part of industry-level dynamics, in terms of employment as well as productivity growth. Existing studies hint at the crucial role that credit constraints and demand-side factors can play in hampering post-entry growth. The trade-off which - to some extent- appears to exist between employment and productivity growth complicates the formulation of a coherent policy as policies that aim at raising productivity may offset measures that seek to ensure the employability of low productivity workers. Martin and Scarpetta (2012) argue that reforms of stringent employment protection should be part of a comprehensive policy that also includes adequate support for the unemployed.

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