Small Bus Econ
DOI 10.1007/s11187-015-9655-z

Productivity, market selection, and corporate growth: comparative evidence across US and Europe

Giovanni Dosi · Daniele Moschella · Emanuele Pugliese · Federico Tamagni

Accepted: 7 March 2015

Abstract This paper analyses the patterns of market selection in manufacturing industries of France, Germany, UK, and USA. We first disentangle the contribution to industry-level productivity growth of *within*-firm productivity changes and *between*-firm reallocation of shares. The evidence corroborates the notion that within-firm learning prevails over market selection forces, with larger firms driving such innovation and learning processes. Second, we address the "strength" of selection by exploring to what extent firm growth rates are shaped by relative productivity levels as compared to variation thereof. Our key finding is that, although changes in relative efficiency have a greater impact on growth than relative efficiency levels, there is an overall weak relationship between productivity and growth and, therefore, a weak power of selection forces in all countries. The results hold across firms of different size, but we also find that selection bites more on SMEs.

Keywords Firm heterogeneity · Productivity decomposition · Corporate growth · Market selection · Learning · Firm–industry dynamics

JEL Classifications C23 · D22 · L10 · L20 · O47

G. Dosi (✉) · D. Moschella · E. Pugliese · F. Tamagni
Institute of Economics, Scuola Superiore Sant'Anna, Piazza Martiri della Libertá 33, 56127 Pisa, Italy
e-mail: gdosi@sssup.it

1 Introduction

Several empirical studies have documented by now the turbulent micro-dynamics underlying the process of productivity growth in manufacturing sectors, finding significant rates of input and output reallocation across firms, even within relatively narrowly defined industries. In interpreting such evidence, a central concern has been the relative importance for aggregate productivity of, first, the reallocation of market shares across differently productive incumbent firms—the so-called *between* effect; second, firm-specific productivity gains or losses by the incumbent firms—the so-called *within* effect; and third, the turnover between entrant and exiters.[1]

The between component is commonly viewed as a measure of market-driven selection, in agreement with the intuition that market shares reallocation across firms should proceed in favour of more productive firms (or plants), while less productive units are expected to see their market share shrinking. This view that markets work as selectors of "better firms" is indeed pervasive in theories of firm-industry evolution, which agree in predicting a positive association between growth of a firm and its relative efficiency, due to competitive selection forces delivering gains and losses according to heterogeneous and firm-specific efficiencies. However, the empirical

[1] See Bartelsman and Doms (2000), Dosi (2007), and Syverson (2011) for surveys and discussions.

evidence suggests that the between component usually provides a smaller contribution to productivity growth than the within term, hinting at a relative weakness of selection forces as compared to the impact of idiosyncratic learning.

The central contribution of this paper regards indeed the identification of the strength of market-driven selection. We address two major limitations of the existing empirical literature.

First, most studies in the productivity decomposition literature focus on specific countries or industries, adopting different decomposition methods, thus making a comparison of the findings far from straightforward.[2] In the present study, the analysis is based on an invariant methodology, consistent across sectors and across countries, and we apply that to the same unit of analysis, i.e. at the firm level. By comparing results across the USA and three major European economies, namely France, Germany, and the UK, we seek to reveal similarities and differences across economies characterized by different industrial and institutional structures, plausibly influencing also the features and intensity of the selection processes.

Second, we want to deeper analyse the micro-drivers of selection dynamics. Indeed, the between component of aggregate productivity decompositions gives only a quite indirect and imprecise measure of selection among incumbents. It just quantifies that part of aggregate productivity changes (say at sectoral level) which is accounted for by market share changes correlated with firm-specific differentials from average productivity. A finer and more direct empirical assessment of market selection forces concerns the extent to which firm-specific relative productivities influence the relative growth performance of firms. We therefore turn to direct estimation of the relationship between relative efficiency and growth rates through firm-level regressions. The empirical literature has rarely followed this route, perhaps influenced by the theoretical agreement that firm growth and firm efficiency are positively and strongly correlated. One of the first exceptions, to our knowledge, is in Bottazzi et al. (2010), finding that the relationship between growth and (labour) productivity is indeed weak in a large sample of French and Italian manufacturing firms, suggesting equally weak strength of market selection forces. A much greater room of explanation is left to unobserved heterogeneity, ultimately capturing both idiosyncratic degrees of "strategic freedom" of individual firms and, together, the sheer ignorance of the researcher on the underlying drivers of the process.[3]

We share with that study the intuition that switching from decompositions to firm-level regression represents a crucial step forward, and we follow the same strategy to quantify the workings of selection via an assessment of the explanatory power of productivity as a predictor of firm growth. However, we extend the analysis along several lines. First, we work with data about firms from four different countries allowing us to explore invariances and diversities across the two major continental Europe economies (Germany and France) and two more "free-market" oriented economies (the UK and the USA). Second, fixed effects estimates presented in that study can severely underestimate the true contribution of relative efficiency, since the within transformation washes away the average efficiency of a firm over the observed period. We instead resort to correlated random effects regressions, allowing us to also consider the contribution of firm-specific average productivity and thus capturing the somewhat structural, time-invariant efficiency effect on growth. Third, while that study only accounts for contemporaneous productivity–growth relationship, we investigate its intertemporal structure, through the inclusion of lags of productivity regressors and also by looking at longer-run relationship between average growth and average productivity performances computed over the sample period. Fourth, and finally, we assess the relative importance of relative productivity *levels* versus relative productivity *changes* over time as apparent determinants of firm growth.

A further concern of our study is also to unravel the role of firm size, seeking to identify whether selection dynamics present specificities across small–medium enterprises (SMEs) as compared to larger firms. A vast literature indeed suggests that SMEs can represent a key driver of economic growth—or at least the more

[2] See Foster et al. (2001) for a discussion of sensitivity of decomposition results to different methodologies and Petrin and Levinsohn (2012) for specific treatment of decompositions based on plant-level data.

[3] See also Bottazzi et al. (2008) for a more descriptive analysis of Italian manufacturing based on rank correlation, also suggesting weak competitive selection.

dynamic and more innovative subset of them—especially when young and able to survive to the first years after entry. At the same time, however, small firms tend to face major constraints to growth, especially because of their lower ability to get finance, and the difficulties that can arise in managing crucial stages of development concerning, e.g. internationalization and formalization of R&D and other innovative activities. It is therefore a priori not trivial whether one should expect selection to be stronger for (surviving) SMEs. Our analysis addresses this question and provides an original attempt, to our knowledge, to identify the SMEs' contribution to the within and between components of overall sectoral productivity growth.

Our main findings reveal an overall weak power of selection forces, emerging robustly in all countries. First, from the decomposition of sectoral productivity growth, we confirm previous evidence of a prevalence of the within-firm effect over the between component, corroborating the notion that within-firm learning processes offer a more relevant contribution than market selection to the overall productivity dynamics. A major qualification comes from the result that the within-firm component is larger across larger firms than across SMEs, suggesting larger firms drives learning and innovation processes. Second, our firm-level regressions show that, although relative productivity changes exert a greater influence than relative productivity levels, such productivity variables together provide little association with firm growth rates, contrary to most common theoretical expectations. Notably, such a result of a weak working of selection holds across firms of different sizes, although competitive selection is fiercer across small–medium firms.

2 Background literature

The empirical identification of the role of markets as efficient selectors of the better performing business units is not easy. The commonly followed approach rests upon the properties of longitudinal micro-data (at firm or plant level), apt to decompose aggregate (economy or sector wide) productivity changes. In such decomposition, market selection forces are captured by the contribution coming from reallocation of market shares across heterogeneously efficient incumbent units (the so-called between component), and its power is assessed against the aggregate productivity changes coming from incumbent firms increasing or decreasing their efficiency (the within component), or coming from the "churning" associated with entry and exit dynamics.

The overall picture emerging from this literature is that industrial dynamics is shaped by significant rates of input and output reallocation across firms, even within relatively narrowly defined industries (see Baily et al. 1992; Griliches and Regev 1995; Foster et al. 2001; Baldwin and Gu 2006, among others). The process is also characterized by high flows of entry and exit, with about half of the new firms dying within the first 5 years (Bartelsman et al. 2005). Together, the decomposition exercises provide mixed evidence on the contribution of this "churning" to the overall productivity growth, with some studies finding small effects (see Baily et al. 1992; Griliches and Regev 1995, for USA and Israel, respectively) and others showing more sizable ones (see Baldwin and Gu 2006, on Canada).[4] There is instead more agreement in the finding that the between effect usually provides a smaller contribution to aggregate productivity growth than the within term. In fact, some evidence, as in Disney et al. (2003) for the UK or in Baldwin and Gu (2006) for Canada, shows even negative between term.

How does one interpret all this? First, start from the premise that the between term in standard aggregate productivity decompositions cannot be a satisfactory measure of selection. A finer underlying question involves a direct estimation of the relationship between relative productivity and firm growth. The efficiency–growth relationship is at the core of heterogeneous firms models of industry dynamics rooted into different theoretical camps, which all tend to agree in predicting a positive and strong association between growth of a firm and its relative efficiency. This applies to models of "equilibrium evolution" such as the by now classical Jovanovic (1982), Hopenhayn (1992) and Ericson and Pakes (1995), to the more recent Luttmer (2007) and Acemoglu et al. (2013). And it does also apply to Schumpeterian

[4] Plehn-Dujowich (2009) extends the standard framework to also incorporate reallocation across industries, that is looking at existing firms exiting from one industry and reallocating their assets via entry into a different industry or opening a new product line.

evolutionary models, including the classic Nelson and Winter (1982), and also a family of models formally representing the process of selection among firms through some mechanism of the replicator dynamics type. So, for example, in an evolutionary framework *à la* Silverberg et al. (1988), if competitiveness is inversely related to prices, in turn inversely related to productivity, then the law of motion of shares of firm i in any one industry is described by a replicator dynamics of the form

$$\Delta s_{i,t} = f(\pi_{i,t} - \bar{\Pi}_t) s_{i,t-1}, \tag{1}$$

where Δ stands for first difference, $s_{i,t}$ is the market share of firm i at time t, $\pi_{i,t}$ is the productivity of firm i, and $\bar{\Pi}_t$ the average industry productivity. With all agnosticism on the functional form of f, granted monotonicity, firms with above-average productivity should display above-average growth and increase their market shares, and viceversa for less productive firms.[5]

The empirical literature has not given the deserved attention to the analysis of the growth–productivity relationship at the firm level. In one of the first systematic attempts, Bottazzi et al. (2010) specify a relationship between firm growth and contemporaneous relative productivity. Exploiting large samples of French and Italian manufacturing firms, they estimate the equation via a standard fixed effects within-group estimator and then compute a modified R^2 accounting for the contribution of contemporaneous productivity to the total variance of firm growth in different sectors. They find that relative productivity "explains" roughly between 3 and 5 % of the variance in growth rates, while the contribution of unobserved heterogeneity (the firm fixed effects) is much larger. As we shall see in the following, our analysis supports their general conclusion that selection forces are indeed weak, although we account here for the dynamic structure of the productivity–growth relationship and we exploit correlated random effects estimator to correct for fixed effects estimates neglecting the potentially important role of the time-invariant component of firm-specific productivity, capturing structural differences across firms.

3 Data and variables

The analysis draws upon two largely used firm-level datasets. For US firms, our source is the North American section of COMPUSTAT. This is a well-known and widely used dataset covering all firms listed on US stock exchange, available to us starting from the year 1958. For the European countries (France, Germany, and the UK), we use AMADEUS, a commercial database provided by Bureau van Dijk. The edition at our access (March 2010) contains balance sheets and income statements about over 14 Million European firms over the period 2000–2009. AMADEUS data are standardized to allow comparisons across countries and include up to ten years of accounting information of firms that are legally required to file their accounts. Because of different disclosure rules, coverage varies across countries. Moreover, the yearly update drops all the firms for which there is no information in the previous five years, so that coverage also varies over time.

We are interested in corporate performances across countries as revealed by two major dimensions, namely productivity and growth. We measure firm growth as the log difference of (constant price) sales in two consecutive years. As a measure of productivity, we mainly use the simple ratio of value added, at constant prices, over the number of employees.[6] Figures on employment are readily available in both AMADEUS and COMPUSTAT. Value added, defined in a standard way as revenues minus costs of inputs (labour excluded), is directly computed in AMADEUS data, while only sales and total costs (cost of labour included) are available in COMPUSTAT. Therefore, in order to get a homogeneous proxy for value added, we need to build a measure of cost of labour, and add it

[5] See also Dosi et al. (1995), Silverberg and Verspagen (1995), Metcalfe (1998), among others, for models sharing the same structure. Models in the Nelson and Winter (1982) formalism yield the same qualitative prediction in that more efficient (productive) firms operating in a competitive, price-taking market would get higher profits and (under some reasonable assumption of imperfect capital markets) would invest and produce more relative to the universe of competitors (see also Bottazzi et al. 2001).

[6] Indeed, as one argues at greater length in Dosi and Grazzi (2006), total factor productivity (TFP) measures of productivity might be biased and misleading in the presence of technologically heterogeneous firms and complementarity among inputs. As a robustness check, however, we also repeat our main regression analysis with a TFP index, yielding qualitatively similar conclusions (see Appendix 2).

Table 1 Observations, average and median of growth, productivity, and size

	Growth			Productivity			Size					
	#Obs	Mean	Median	#Obs	Mean	Median	#Obs Empl ≤ 250	Mean	Median	#Obs Empl > 250	Mean	Median
France	69,619	0.036	0.033	92,777	45.19	39.34	83,073	62.76	43	9,794	1,151.9	480
Germany	110,180	0.060	0.010	30,026	68.26	55.34	39,737	89.54	73	11,710	2,482.3	510
UK	103,014	0.039	0.034	75,967	47.35	40.26	60,532	90.66	75	15,785	1,679.5	508
USA	21,211	0.101	0.077	18,225	74.54	60.94	6,275	101.86	92	14,275	12,556	2,235

For each country, the table reports the average and median of growth of sales, labour productivity, and size (as number of employees, distinguishing below and above 250 employees). Figures are computed over non-missing firm-year observations, pooling over years and sectors. Labour productivity figures are all in Euro, measured in real terms (base year and exchange rates in 2005)

back to the difference between sales and total costs. Following Brynjolfsson and Hitt (2003), we compute the cost of employees by multiplying the number of employees times the average sectoral cost of labour as reported by the US Bureau of Labor Statistics (BLS) at the 4-digit level of disaggregation.[7]

In order to have a time interval with a good coverage of the variables of interest in AMADEUS, the empirical analysis spans over the period 2000–2007 for France and UK, while the sample period is 2001–2007 for Germany. Accordingly, we take the years 2000–2007 as the reference also for US firms tracked in COMPUSTAT data. We concentrate the analysis on manufacturing industries, disaggregated according to the ISIC Rev. 4 classification at 2 digits. Although our datasets are known to be more representative of medium-large firms as compared to the reference populations, no minimum threshold is imposed on employment by the data collection process in order to enter the datasets, so that we do have even very small firms in the sample. We however drop micro-firms with <20 employees to keep comparability with Bottazzi et al. (2010).

The final working sample is an unbalanced panel of 36,144 firms, of which 15,371 in France, 7,296 in Germany, 10,428 in the UK from AMADEUS and 3,049 firms from US-COMPUSTAT. We cannot distinguish "true" entry/exit from missing values due to any other reason, since the datasets do not have detailed information on firm demography. However, about 50 % of the firms in all countries are observed for at least 6 years. As reference, consider that for the year 2005, we cover 68 % of total manufacturing employment in France, 72 % in Germany, 55 % in the UK, and 79 % in the USA. Similarly, the share of value added is 60 % in France, 62 % in Germany, 42 % in the UK, and 82 % in the USA.[8]

In Table 1, we present information about number of observations, mean and median of growth of sales, labour productivity, and size (number of employees). We observe differences across countries for all of the main variables, a fact that further motivates our choice to run separate estimates by country. Such differences do not seem to reveal completely different and incomparable structures across countries, as indeed median values are similar, apart for the relatively larger median size of firms in the US sample, reflecting the publicly traded nature of firms in US-COMPUSTAT data. Notice that we do have both large and SMEs firms also in this dataset, however.

Table 2 reports about the degree of within-sector dispersion of firm growth and (log) labour productivity. We confirm the usual stylised facts about the huge firm heterogeneity in terms of both variables, invariably found in other empirical studies even within narrowly defined industries (see, among others, Bartelsman and Doms 2000; Bottazzi and Secchi 2006; Dosi 2007). On average, the standard deviation of growth rates goes from around 20 % in France to 40 % in the UK. Firms are even more differentiated in terms of (log) labour productivity: the across-sectors average of the standard deviation goes from around 0.50 in France and Germany, to 0.55 in the USA, and to almost 0.60 in the UK. This implies,

[7] Constant price sales and value added are obtained by deflating all nominal variables with appropriate sectoral price indexes, from EUROSTAT and from the BLS (base year 2005).

[8] Aggregate country-level data are from OECD STAN database. Coverage is similar in other years.

Table 2 Growth and labour productivity, standard deviations

	France		Germany		UK		USA	
	$stdev(g_i)$	$stdev(\pi_i)$	$stdev(g_i)$	$stdev(\pi_i)$	$stdev(g_i)$	$stdev(\pi_i)$	$stdev(g_i)$	$stdev(\pi_i)$
Food	0.20	0.47	0.25	0.56	0.35	0.58	0.28	0.49
Beverages	0.20	0.71	0.28	0.55	0.38	0.90	0.23	0.65
Textile	0.20	0.47	0.25	0.42	0.39	0.57	0.18	0.28
Wearing	0.23	0.67	0.22	0.64	0.47	0.73	0.21	0.56
Leather	0.20	0.42	0.20	0.48	0.46	0.54	0.25	0.60
Wood	0.17	0.42	0.31	0.31	0.37	0.42	0.22	0.67
Paper	0.15	0.43	0.27	0.52	0.31	0.54	0.18	0.40
Printing	0.20	0.36	0.23	0.46	0.42	0.47	0.21	0.61
Coke and petroleum	0.09	0.63	0.22	0.60	0.37	0.70	0.26	0.83
Chemical	0.20	0.58	0.24	0.53	0.35	0.64	0.28	0.61
Pharmaceutical	0.22	0.62	0.31	0.51	0.39	0.71	0.81	0.81
Rubber and plastic	0.18	0.42	0.25	0.40	0.34	0.53	0.27	0.37
Other non-metallic	0.17	0.46	0.25	0.53	0.37	0.55	0.24	0.48
Basic metals	0.19	0.49	0.20	0.45	0.40	0.50	0.31	0.52
Fabricated metal	0.21	0.35	0.28	0.48	0.40	0.49	0.26	0.44
Machinery	0.22	0.41	0.34	0.44	0.43	0.52	0.30	0.56
Computer and electronic	0.28	0.53	0.33	0.53	0.48	0.63	0.41	0.67
Electrical	0.23	0.45	0.43	0.58	0.43	0.58	0.34	0.53
Motor vehicles	0.22	0.48	0.28	0.51	0.44	0.57	0.24	0.42
Other transport	0.26	0.52	0.38	0.47	0.52	0.55	0.37	0.48
Furniture	0.17	0.40	0.30	0.34	0.39	0.47	0.17	0.45
Other manufacturing	0.23	0.46	0.25	0.58	0.42	0.55	0.35	0.64
Average	0.20	0.49	0.28	0.49	0.40	0.58	0.29	0.55

For each country and sector, the table reports the average of annual standard deviation of sales growth (g_i) and log labour productivity (π_i)

for instance, that in the UK, on average, a firm with labour productivity of 1 standard deviation above the sectoral mean is more than three times more productive than a firm with productivity of about 1 standard deviation below the sectoral mean.

4 Decomposition of productivity growth

Within the standard decomposition approach, industry-level productivity growth is the aggregate outcome of micro-dynamics involving productivity changes and market shares reallocation across incumbents, entering and exiting firms. Incumbent firms, in particular, contribute to aggregate growth by means of two distinct processes. On the one hand, the so-called *within component* captures firm-specific productivity improvements (or losses), and it is interpreted as a measure of the importance for aggregate productivity growth of the processes of learning, innovation, imitation (or lack thereof) taking place inside the firms themselves. On the other hand, the so-called *between component* accounts for the total sum of the (positive or negative) changes in market shares of incumbents weighted by their productivity, and it is interpreted as a measure of the strength of selection forces yielding rewards and punishments—in terms of market shares—according to relative efficiencies.

The relative magnitude of the two components represents our first piece of evidence on the importance of market selection mechanisms. We start from a general index of the aggregate productivity of sector j in year t, $\Pi_{j,t}$, defined as a weighted sum of individual firms' productivities

$$\tilde{\Pi}_{j,t} = \sum_{i \in j} s_{i,t}\pi_{i,t}, \tag{2}$$

where $\pi_{i,t}$ is the labour productivity of firm i in year t and the weight $s_{i,t}$ represents the share of firm i in sector j in the same year. We here measure s_i in terms of employment shares, since this choice ensures that we are decomposing a standard aggregate labour productivity index, as it is indeed done in several previous studies. However, looking at shares of labour inputs might not be the most appropriate way to account for the process of selection: firms do primarily compete in the goods market, and thus, the very working of selective forces might be better revealed in terms of contraction or expansion of sales shares, not employment shares. We shall turn to the dynamics of firm growth as measured by sales in the panel regressions of the next section.

We next decompose the change in the aggregate index $\tilde{\Pi}$ as follows

$$\Delta\tilde{\Pi}_{j,t} = \sum_{i \in j} \bar{s}_i \Delta\pi_{i,t} + \sum_{i \in j} \Delta s_{i,t}\bar{\pi}_i, \tag{3}$$

where Δ stands for the first difference between two subsequent years, and a bar over a variable indicates the average of the variable computed over the two years considered. The first term on the right-hand side is the *within-firm* effect, i.e. the sum of firm-specific changes in productivity weighted by the average market share of each firm. The second term is the *between-firm* effect, i.e. the sum of the variation in firms' shares weighted by average productivity levels. Since by construction the sum of shares of incumbent firms is constant and equal to one, the between term captures the extent to which shares reallocate to firms that stay above or below the average industry productivity.[9]

We can next compute the overall contribution of the two components just by repeating the decomposition for each pair of consecutive years in the sample and then summing over the years, yielding

$$\sum_t \Delta\tilde{\Pi}_{j,t} = \sum_t \sum_{i \in j} \bar{s}_i \Delta\pi_{i,t} + \sum_t \sum_{i \in j} \Delta s_{i,t}\bar{\pi}_i, \tag{4}$$

where, again, the within and between components are the two terms of the sum on the right-hand side.

To ease comparison of the relative importance of between and within effects obtained from Eq. (4), we report percentage shares of the two components in total productivity change.[10] Detailed results according to sectors and countries are presented in Table 3. The "violin plots" in Fig. 1 offer a summary picture. For each country, they combine a standard box plot, reporting the median and the interquartile ranges of the distribution of sectoral estimates within a country, with a kernel estimate of the same distribution, depicted as the contour of the violin. White violins refer to the sectoral distribution of the percentage shares of the between components, while shaded violins show the corresponding distribution of the within terms.

The most robust finding is the strong predominance of the within component. This result is in line with previous works performing decomposition exercises, and it already witnesses against any simplistic view of the power of market selection. Let us emphasize that the pattern holds irrespective of the country considered. Indeed, the median values of the between component computed across sectors are quite low everywhere (10 % in France, 6 % in the UK, 9 % in the USA, and −1 % in Germany), and the distribution of the two components (cf. the violins) are largely overlapping across countries: above 50 % and centred around 1 for the within term, while below 50 % and centred around zero for the between term.

Prima facie, therefore, it seems that weak selection is a robust property invariant across different institutional and other country-specific features. Somewhat contrary to the common wisdom, selectivity of markets does not seem to be more effective in more "market-oriented" economies, such as the UK and the

---

9 Since application of the formula requires information on two consecutive years, incumbent firms need here to be intended as firms for which data for at least two consecutive years are available. Also recall that we cannot properly distinguish entry and exit from simple missing values in one of the variables, so we cannot meaningfully compute the contribution from entry and exit. Further notice that our decomposition, as in Griliches and Regev (1995), does not separate out the covariance effect. It is easy to show that formula (3) splits the covariance term in equal parts between the within and the between components.

10 Notice that the percentage contribution of each component obtained with our formula is equivalent to the weighted sum of the yearly contributions. Take for example the within component. Its total contribution is equal to $\left(\sum_t \sum_{i \in j} \bar{s}_i \Delta\pi_{i,t}\right) \Big/ (\sum_t \Delta \tilde{\Pi}_{j,t}) = \sum_t \left[\left(\frac{\sum_{i \in j} \bar{s}_i \Delta\pi_{i,t}}{\Delta\tilde{\Pi}_{j,t}} \right) \left(\frac{\Delta\tilde{\Pi}_{j,t}}{\sum_t \Delta\tilde{\Pi}_{j,t}} \right) \right]$.

Table 3 Decomposition of sectoral productivity

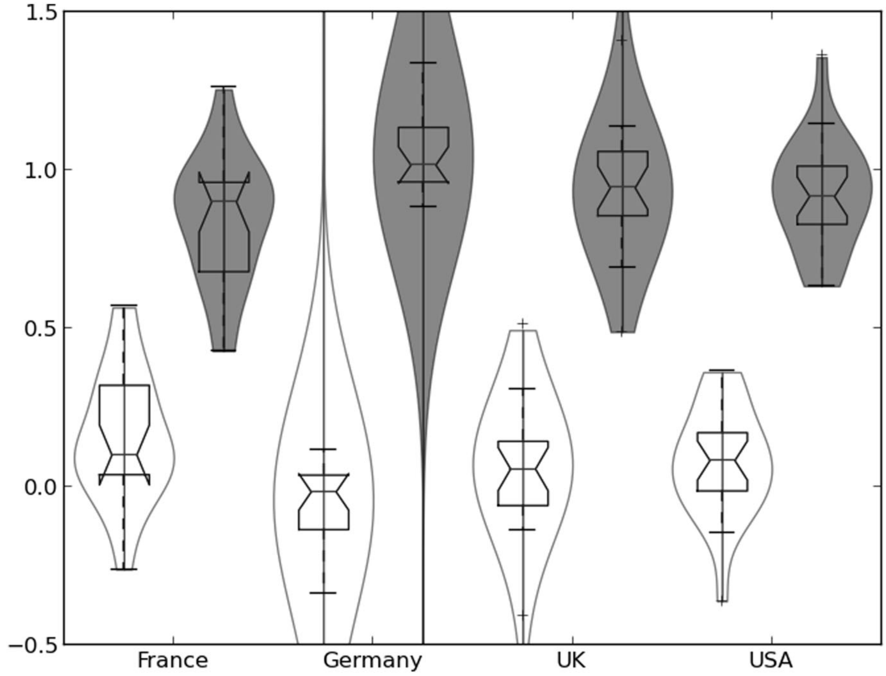
	France		Germany		UK		USA	
	Within	*Between*	*Within*	*Between*	*Within*	*Between*	*Within*	*Between*
Food	1.26	−0.26	0.88	0.12	1.41	−0.41	0.78	0.22
Beverages	0.98	0.02	1.34	−0.34	1.08	−0.08	1.06	−0.06
Textile	0.43	0.57	1.28	−0.28	2.53	−1.53	1.11	−0.11
Wearing	0.67	0.33	−1.59	2.59	0.80	0.20	0.82	0.18
Leather	0.44	0.56	0.97	0.03	1.07	−0.07	0.72	0.28
Wood	0.92	0.08	0.96	0.04	0.91	0.09	1.36	−0.36
Paper	0.90	0.10	2.04	−1.04	0.98	0.02	1.14	−0.14
Printing	0.64	0.36	0.96	0.04	0.69	0.31	0.63	0.37
Coke and petroleum	1.05	−0.05	1.22	−0.22	1.14	−0.14	0.91	0.09
Chemical	0.86	0.14	0.96	0.04	0.97	0.03	0.87	0.13
Pharmaceutical	0.97	0.03	1.82	−0.82	1.04	−0.04	1.01	−0.01
Rubber and plastic	0.97	0.03	1.08	−0.08	0.77	0.23	1.06	−0.06
Other non-metallic	0.90	0.10	0.91	0.09	0.81	0.19	0.92	0.08
Basic metals	0.92	0.08	1.00	−0.00	1.07	−0.07	0.89	0.11
Fabricated metal	0.79	0.21	1.02	−0.02	0.90	0.10	1.00	0.00
Machinery	0.92	0.08	0.99	0.01	0.90	0.10	0.88	0.12
Computer and electronic	0.65	0.35	1.03	−0.03	0.49	0.51	0.70	0.30
Electrical	1.13	−0.13	1.08	−0.08	0.92	0.08	1.01	−0.01
Motor vehicles	0.94	0.06	1.06	−0.06	0.96	0.04	0.95	0.05
Other transport	0.82	0.18	0.96	0.04	0.97	0.03	1.01	−0.01
Furniture	0.72	0.28	1.15	−0.15	0.86	0.14	0.65	0.35
Other manufacturing	0.66	0.34	1.01	−0.01	0.86	0.14	0.86	0.14
Average	0.84	0.16	1.01	−0.01	1.01	−0.01	0.92	0.08
Median	0.90	0.10	1.01	−0.01	0.94	0.06	0.92	0.09

Decomposition as from Eq. (4), over the period from 2000 (2001 for Germany) to 2007. Reported values are normalized as shares of aggregate sectoral productivity change

USA, as compared to continental Europe, at least to the extent that the between component can capture all that. Note also that a negative between term, as it is in quite a few sectors, implies that shares in terms of employees are reallocated to *less* productive firms. This seems to be more frequent in Germany, a fact that may be connected to the process of restructuring and reforms undergone in the country over the period of observations.

At the same time, there does not seem to be any robust link between competitive selection forces and sectoral specificities. This result is striking, too, since a priori one could think that some sectors should be characterized by more turbulent dynamics and more aggressive competitive selection. However, we find that the between component of a given sector can sensibly vary across countries. Take, for instance, a commonly considered low-tech and mature sector like "textile". Here, we find one of the highest between effect in France (0.57), but a negative between effect in all other countries. Similarly, "computer and electronics", which we can consider as one of the most high-tech and dynamic sectors, displays a 51 % contribution of the between effect to total productivity change in the UK, but much lower values (around 30 % in France and in the USA) and a small and negative (−3 %) contribution in Germany. Spearman's rank correlations computed between the distributions of the between components for pairs of countries confirm the lacking presence of strong sectoral specificities (see Table 4). The coefficients are all small and not statistically different from zero in most cases. The correlation is significant, yet not perfect (0.5) only in the Germany–USA comparison,

Fig. 1 Distributions of sectoral *between* and *within* components as from decomposition in Eq. (4), by country. For each country, the *white* and the *shaded* violin refers to the between and within component, respectively. Each violin reports a box plot and a kernel density to each side of the box plot. Distributions, median values, and interquartile ranges as from Table 3



suggesting some more similarity in the sectoral ranking of selection forces between these two countries.

5 Regression analysis

Despite the standard practice to interpret productivity change decompositions as an assessment of the relative importance of selection/reallocation versus firm-specific learning, a more natural way to address the workings of selection is to directly look at the productivity–growth relationship within a standard firm-level regression framework. Refining upon Bottazzi et al. (2010), in this section we look at the strength of the market selection by estimating the explanatory power of productivity as predictor of firm growth. Our main specification accounts for the overall explanatory power of current and lagged levels of relative productivity upon corporate growth. Next, we consider the relative explanatory power of relative productivity levels vs. over time changes of relative productivities. Finally, we offer a "longer-run" picture, by investigating the relationship between firm-specific average growth and average productivity computed over sub-periods. In all the exercises, we

Table 4 Between effect: rank correlation across countries

	France	Germany	UK	USA
France	1.00	0.23	0.35	0.38
		(0.29)	(0.11)	(0.08)
Germany		1.00	0.31	0.50
			(0.15)	(0.02)
UK			1.00	0.36
				(0.10)
USA				1.0

Spearman's rank correlation coefficients between sectoral *between* effects across countries. Significance levels in parenthesis

define firm growth in terms of growth of sales, a measure that directly links to the success (or failure) on the product market, and we provide separate estimates by the different sectors within each country.

5.1 Main results: firm growth and relative productivities

We start from a general specification of the growth–productivity relationship as a linear model with additive heterogeneity

$$g_{i,t} = a + b_t + \sum_{l=0}^{L} \beta_l \pi_{i,t-l} + u_i + \epsilon_{i,t} \tag{5}$$

where $g_{i,t}$ denotes the growth rate of firm i in terms of log differences of sales between year t and $t-1$, $\pi_{i,t-l}$ captures current and past labour productivity with L the longest lag length considered ($l = \{0, \ldots, L\}$), b_t is a year dummy, u_i captures firm-specific time-invariant unobserved heterogeneity, and $\epsilon_{i,t}$ is a usual error term. Since we shall run separate regression by sectors and countries, the presence of time dummies is equivalent to consider the variables in deviation from their yearly cross-sectional average within industry (and countries), so that relative efficiency within industries (and countries) is what matters for relative firm growth, in accordance with a replicator dynamics type of relationship as in Eq. (1).[11]

There may be different strategies to estimate Eq. (5) in practice. Bottazzi et al. (2010) choose a specification with current productivity π_t as the only regressor and apply a standard fixed effects within estimator. We employ a different strategy. First, we want to keep a specification allowing for distributed lags in the effects of the independent variable, picking up possible adjustment times between changes in relative productivities and changes in the growth rates.[12]

Based on sequential rejection of the statistical significance of longer lags structure, we specify the following regression equation with $L = 1$ as our baseline model

$$g_{i,t} = a + b_t + \beta_0 \pi_{i,t} + \beta_1 \pi_{i,t-1} + u_i + \epsilon_{i,t}. \tag{6}$$

Second, we apply the Mundlak's (1978) version of the correlated random effects estimator. That is, we estimate via random effects the following model

$$\begin{aligned} g_{i,t} = a + b_t + \beta_0 \pi_{i,t} + \beta_1 \pi_{i,t-1} + \beta_{0a} \bar{\pi}_i \\ + \beta_{1a} \bar{\pi}_{i,-1} + c_i + \epsilon_{i,t}, \end{aligned} \tag{7}$$

where we add $\bar{\pi}_i$ and $\bar{\pi}_{i,-1}$, respectively indicating the within-firm time series averages of the (log) productivity up to time t and to time $t-1$, while c_i is a new unobserved firm-specific heterogeneity term, uncorrelated with the productivity regressors after controlling for their averages.

The fixed effects within-group estimator applied to Eq. (6) and the random effects estimates of Eq. (7) return exactly the same point estimates of the coefficients β_0 and β_1, as shown in Mundlak (1978) for balanced panel and in Wooldridge (2009) for the unbalanced case. The main advantage of the correlated random effects estimator is that the fixed effect model systematically neglects the "productivity-related contribution" hidden within the firm-specific term u_i. To see why this is important, consider the case of two firms with the same productivity dynamics through time, but different *average* productivity. If the firm with the higher average productivity grows more, within-group estimation imputes this "productivity premium" to the firm-specific, time-invariant unobserved factors, while this average effect should be clearly considered as part of the explanatory power of productivity. Correlated random effects exactly allow to account for that component. And indeed, what we primarily focus on is not just the point estimate and significance of β_0, β_1 and of the other coefficients. Rather, we are more interested in the "overall" contribution of productivity to sales growth, which we quantify via the following measure of the fraction of total variance explained by productivity terms

$$S^2 = \frac{\mathrm{Var}\left(\beta_0 \pi_{i,t} + \beta_1 \pi_{i,t-1} + \beta_{0a} \bar{\pi}_i + \beta_{1a} \bar{\pi}_{i,-1}\right)}{\mathrm{Var}(g_{i,t})}. \tag{8}$$

The traditional coefficient of determination

$$R^2 = \frac{\mathrm{Var}\left(\beta_0 \pi_{i,t} + \beta_1 \pi_{i,t-1} + \beta_{0a} \bar{\pi}_i + \beta_{1a} \bar{\pi}_{i,-1}\right) + Var(c_i)}{\mathrm{Var}(g_{i,t})} \tag{9}$$

[11] In preliminary analysis, we have also explored the validity of the linear specification. Kernel regressions show that the linear fit is in the 95 % confidence interval across sectors and countries, and the lack of nonlinearities is confirmed by a parametric binned regression with three bins for low-, medium-, and high-productivity firms.

[12] Lagged values also help in alleviating violations of strict exogeneity of the error term. Indeed, the presence of significant lags helps in ensuring that there are no shocks to the dependent variable that are correlated with past values of the independent variable. More formally, strict exogeneity $\left(E\left(\epsilon_{i,t} | \pi_{i,s}, u_i\right) = 0, \forall t, s\right)$ also requires that future values of the dependent variable are uncorrelated with present shocks. We tested this hypothesis by including π_{t+1} in our regressions. The coefficients of this variable were not statistically significant in the large majority of the cases.

also includes the contribution of the heterogeneity term c_i, so that the difference between R^2 and S^2 delivers a measure of the variance explained by time-invariant unobserved factors.[13]

Usual caveats are in order, since we recognize that our econometric strategy does not cure all the possible sources of bias that could arise in the estimation. First, our choice to focus on productivity alone allows us to better focus on the explanatory power merely originating from productivity variables, but at the same time obviously exposes the exercise to omitted variable bias. Indeed, firm fixed effects absorb the time-invariant component of the omitted and potentially relevant determinants of growth that can jointly affect productivity. This is not a too heroic hypothesis, however, given the relatively short sample period. Yet, we know that time-varying components of omitted variables may play a role. If this were the case, the most likely implication would be that we are overestimating the effect of productivity terms on growth, since most of standard control variables such as age, R&D, or quality of inputs are all likely to have the same sign in their correlation with both growth and productivity.[14]

A second common source of bias can arise from feedback effects or reverse causality from growth to productivity. There are two theoretically conflicting hypothesis about the potential direction of the bias. Some theories tend to predict that growth should exhibit a positive effect on subsequent productivity, via a sort of micro-level version of Kaldor–Verdoorn law. However, one can also envisage that growth is accompanied by decreasing productivity, due to a "Penrose effect" implying efficiency losses due to difficulties in managing the organization during the growth process (see Coad 2009, for a review of the theories). We have however verified that we can reject that growth Granger-causes productivity, within regressions of productivity against its own past and past growth. In that regression, moreover, the lags of sales growth, when significant, display a positive coefficient, so that, if anything, reverse causality can make us overestimating the effects of productivity. Overall, therefore, we can predict a potential positive bias in our estimates from both omitted variables and reverse causality. This makes any finding of weak correlation between productivity and growth *a fortiori* even stronger. As the following analysis will show, this is precisely our main conclusion.

Table 5 report estimates of the correlated random effects model in Eq. (7), according to sectors and countries. To ease identification of the main patterns, we also provide a graphical summary in Fig. 2 where, for each country, the two shaded violin plots represent the distribution of the sectoral coefficients β_0 (the leftmost violin) and β_1 (the rightmost one) and the white violin in the middle represents the sum of the two coefficients. We observe that, although there is variation in the point estimates, the coefficients β_0 and β_1 are significant at the 1 % level in almost the totality of sectors across the four countries. This suggests that relative productivity levels, both at time t and at time $t-1$, have an effect on firm growth rates. Moreover, strong regularities emerge concerning the magnitudes and the signs of the two coefficients across both sectors and countries. First, the two coefficients are quite stable in absolute value, with a median across sectors of about 0.2 in all the countries. Since β_0 and β_1 are elasticities, we can say that, in median, a 1 % increase in productivity at time t or $t-1$ is related to an average change in sales growth of around 0.2. Second, the estimated β_0 and β_1 tend to be similar in magnitude and to have an opposite sign, as it is apparent from the white violins, all tightly spread around a median value of about zero.

Next, in Table 6, we report the corresponding values of S^2 and R^2, again by countries and industries. The values of R^2 show that our simple linear model with levels and averages of productivity plus firm-level heterogeneity is able to account from around 40 % to about 65 % of the variance in sales growth rates. Median values across sectors are 0.41 for France, 0.65 for Germany, 0.40 for the UK, and 0.52

[13] More precisely, R^2 also considers the contribution of time dummies, whereas S^2 also considers the covariances between time dummies and productivity variables. Year dummies are however found to explain a negligible part of total variation in our case, so that in practice the c_i terms explain the entire difference R^2-S^2.

[14] Also notice that in Sect. 6 below we explore robustness of our main conclusions across firms of different size and that (see Appendix 2) we are also able to confirm our main results when using TFP in place of labour productivity, implicitly controlling for capital intensity. Other potentially interesting controls, such as age and R&D in particular, are unfortunately not available or rather full of missing values in the data, especially in AMADEUS.

Table 5 Productivity–growth relationship, coefficients

	France		Germany		UK		USA	
	β_0	β_1	β_0	β_1	β_0	β_1	β_0	β_1
Food	0.221***	−0.200***	0.271***	−0.347***	0.180***	−0.168***	0.185***	−0.124***
	(0.009)	(0.008)	(0.037)	(0.042)	(0.014)	(0.014)	(0.042)	(0.041)
Beverages	0.207***	−0.137***	0.167**	−0.434***	0.250***	−0.109***	0.292***	−0.266***
	(0.019)	(0.019)	(0.074)	(0.058)	(0.028)	(0.030)	(0.059)	(0.080)
Textile	0.285***	−0.283***	0.265***	−0.247***	0.168***	−0.124***	0.288 **	−0.209
	(0.013)	(0.014)	(0.099)	(0.091)	(0.014)	(0.015)	(0.139)	(0.148)
Wearing	0.246***	−0.193***	0.039	−0.195***	0.212***	−0.144***	0.147***	−0.113***
	(0.016)	(0.016)	(0.070)	(0.065)	(0.022)	(0.024)	(0.034)	(0.034)
Leather	0.387***	−0.375***	0.379***	−0.332***	0.197***	−0.106 **	0.453***	−0.350***
	(0.026)	(0.026)	(0.047)	(0.055)	(0.040)	(0.046)	(0.058)	(0.062)
Wood	0.280***	−0.254***	0.545***	−0.432***	0.165***	−0.197***	0.192***	−0.210***
	(0.013)	(0.013)	(0.102)	(0.084)	(0.021)	(0.022)	(0.031)	(0.057)
Paper	0.107***	−0.119***	0.418***	−0.254***	0.116***	−0.084***	0.285***	−0.272***
	(0.013)	(0.014)	(0.046)	(0.044)	(0.015)	(0.016)	(0.063)	(0.061)
Printing	0.245***	−0.193***	0.210**	−0.061	0.226***	−0.215***	−0.093	−0.317***
	(0.014)	(0.014)	(0.090)	(0.078)	(0.015)	(0.016)	(0.094)	(0.082)
Coke and petroleum	0.000	0.030	0.464***	−0.556***	0.102**	−0.127**	−0.076	−0.068
	(0.043)	(0.039)	(0.124)	(0.096)	(0.052)	(0.050)	(0.058)	(0.061)
Chemical	0.150***	−0.157***	0.195***	−0.174***	0.112***	−0.082***	0.155***	−0.207***
	(0.011)	(0.012)	(0.029)	(0.029)	(0.010)	(0.011)	(0.024)	(0.026)
Pharmaceutical	0.345***	−0.302***	0.259***	−0.151***	0.193***	−0.125***	0.252***	−0.247***
	(0.028)	(0.024)	(0.033)	(0.035)	(0.023)	(0.020)	(0.026)	(0.023)
Rubber and plastic	0.198***	−0.221***	0.133***	−0.161***	0.179***	−0.164***	0.165***	−0.141***
	(0.012)	(0.011)	(0.041)	(0.042)	(0.015)	(0.015)	(0.049)	(0.044)
Other non-metallic	0.256***	−0.262***	0.446***	−0.369***	0.202***	−0.228***	0.136**	−0.260***
	(0.014)	(0.013)	(0.055)	(0.046)	(0.018)	(0.017)	(0.057)	(0.067)
Basic metals	0.242***	−0.257***	0.232***	−0.167***	0.261***	−0.255***	0.139***	−0.160***
	(0.016)	(0.016)	(0.034)	(0.033)	(0.022)	(0.023)	(0.044)	(0.044)
Fabricated metal	0.380***	−0.342***	0.200***	−0.273***	0.234***	−0.213***	0.381***	−0.229***
	(0.008)	(0.008)	(0.033)	(0.030)	(0.011)	(0.012)	(0.038)	(0.039)
Machinery	0.350***	−0.294***	0.297***	−0.199***	0.189***	−0.152***	0.216***	−0.222***
	(0.012)	(0.011)	(0.027)	(0.025)	(0.012)	(0.013)	(0.017)	(0.019)
Computer and electronic	0.249***	−0.239***	0.167***	−0.239***	0.200***	−0.179***	0.249***	−0.154***
	(0.017)	(0.015)	(0.037)	(0.044)	(0.010)	(0.010)	(0.010)	(0.009)
Electrical	0.302***	−0.400***	0.271***	−0.188***	0.210***	−0.204***	0.323***	−0.151***
	(0.018)	(0.018)	(0.037)	(0.033)	(0.014)	(0.015)	(0.047)	(0.041)
Motor vehicles	0.242***	−0.273***	0.133***	−0.240***	0.136***	−0.220***	0.304***	−0.203***
	(0.020)	(0.020)	(0.051)	(0.042)	(0.024)	(0.021)	(0.072)	(0.076)
Other transport	0.240***	−0.282***	0.336**	−0.222	0.154***	−0.107***	0.286***	−0.288***
	(0.030)	(0.029)	(0.143)	(0.156)	(0.020)	(0.020)	(0.065)	(0.062)
Furniture	0.219***	−0.200***	0.635***	−0.630***	0.222***	−0.123***	0.315***	−0.085
	(0.019)	(0.020)	(0.092)	(0.120)	(0.023)	(0.025)	(0.060)	(0.064)
Other manufacturing	0.377***	−0.318***	0.210***	−0.269***	0.200***	−0.205***	0.177***	−0.137***
	(0.020)	(0.023)	(0.057)	(0.043)	(0.012)	(0.012)	(0.025)	(0.020)

Random effects estimates of Eq. (7), robust standard errors in parenthesis

*** $p<0.01$, ** $p<0.05$, * $p<0.10$

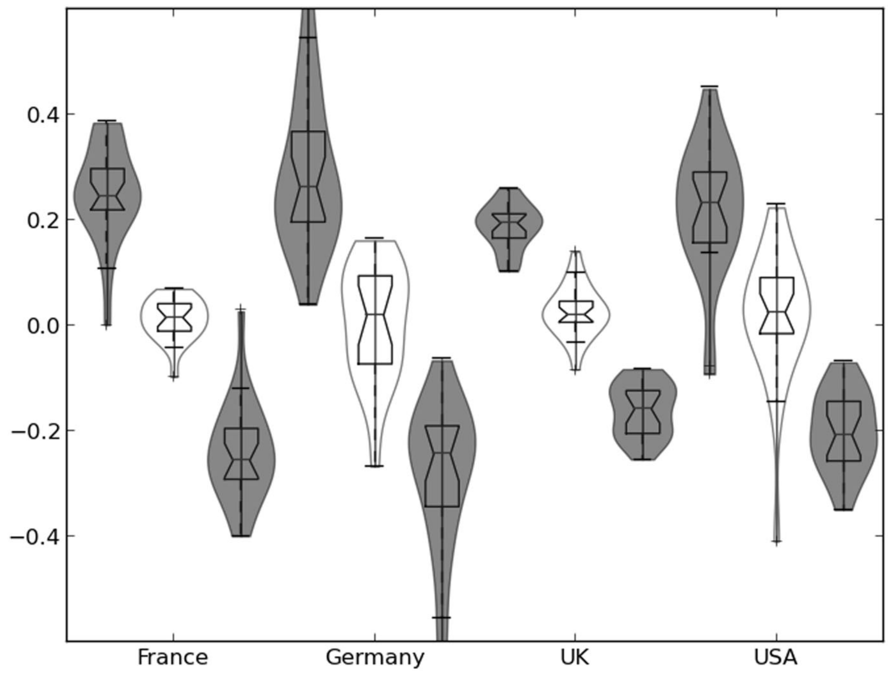


Fig. 2 Distributions of sectoral estimates of β_0 and β_1 from random effects estimation of Eq. (7), by country. For each country the *leftmost* and *rightmost shaded* violins report β_0 and β_1, respectively, while the *white* violin reports $\beta_0 + \beta_1$. Kernel estimates, median values, and interquartile ranges as from Table 5

for the USA. The values of S^2, capturing the contribution of the productivity regressors (both levels and averages), are in median 0.19 for France, 0.18 for Germany, 0.14 for the UK, and 0.15 for the USA. That is, productivity variables account from 1/5 to 1/6 of the variance in firms' growth rates. This is a relatively modest contribution, although considerably higher than found in Bottazzi et al. (2010). Correspondingly, idiosyncratic firm fixed effects have a smaller impact as compared to Bottazzi et al. (2010), but they still account for the major part of the "explained" variance in firm growth. It is difficult to identify robust sectoral specificities. The general tendency is that the value of S^2 for a specific sector varies sensibly across countries, or it may be comparable across pairs of countries, but quite different in others. Spearman's rank correlations (in Table 7) tell that there is a sizable positive and significant (0.74) association between the ranking of the S^2 distributions of France and the UK, while all the other pairwise correlations are not statistically different from zero.[15]

Overall, the regression analysis confirms that selection forces are weak, although we find here somewhat stronger role of efficiency-driven competitive selection as compared to its near absence when measured by the very low (basically zero) share of the between components in the foregoing decomposition exercise. Moreover, as noticed in that exercise, weak competitive selection appears to characterize all of the four economies under study, although one would have expected market forces to bite more in the US and the UK, given the more free-market-oriented structures of these countries as compared to the traditionally more regulated French and German institutional set-ups. Finally, we do not find specific sectors, nor groups of sectors, which display the same pattern in all countries.

5.2 Productivity levels and productivity changes

A seemingly puzzling finding from the above analysis is that the estimated values of S^2 actually result from two opposing effects, a positive one from contemporaneous productivity and a negative one from the lagged variable.[16] One may conjecture that a reason

[15] In Appendix 2, we show that the overall picture does not change if we use a TFP proxy for productivity.

[16] We have verified that the same result is confirmed also if we estimate two separate specifications with $\pi_{i,t}$ and $\pi_{i,t-1}$ alternatively entering as the only regressor, so that the finding does not simply originates from some "perverse" collinearity between current and lagged productivity.

Table 6 Productivity–growth relationship, explained variance

	France		Germany		UK		USA	
	S^2	R^2	S^2	R^2	S^2	R^2	S^2	R^2
Food	0.14	0.38	0.17	0.73	0.09	0.36	0.03	0.51
Beverages	0.16	0.33	0.24	0.60	0.10	0.32	0.19	0.45
Textile	0.23	0.46	0.13	0.66	0.25	0.50	0.05	0.47
Wearing	0.18	0.40	0.06	0.68	0.16	0.39	0.06	0.54
Leather	0.33	0.54	0.38	0.99	0.20	0.46	0.32	0.73
Wood	0.22	0.43	0.26	0.89	0.16	0.42	0.25	0.66
Paper	0.07	0.29	0.28	0.66	0.11	0.38	0.14	0.38
Printing	0.18	0.39	0.03	0.68	0.15	0.42	0.13	0.33
Coke and petroleum	0.03	0.28	0.45	0.70	0.05	0.42	0.19	0.58
Chemical	0.10	0.39	0.16	0.60	0.06	0.40	0.11	0.55
Pharmaceutical	0.26	0.42	0.32	0.61	0.14	0.40	0.18	0.53
Rubber and plastic	0.12	0.33	0.05	0.52	0.11	0.36	0.19	0.53
Other non-metallic	0.24	0.47	0.26	0.66	0.19	0.44	0.10	0.48
Basic metals	0.22	0.45	0.17	0.61	0.21	0.42	0.12	0.57
Fabricated metal	0.24	0.45	0.18	0.69	0.13	0.37	0.28	0.66
Machinery	0.24	0.42	0.12	0.57	0.13	0.34	0.19	0.50
Computer and electronic	0.19	0.44	0.05	0.60	0.13	0.41	0.17	0.54
Electrical	0.26	0.44	0.15	0.56	0.15	0.38	0.09	0.44
Motor vehicles	0.17	0.38	0.11	0.59	0.14	0.39	0.05	0.28
Other transport	0.16	0.37	0.07	0.45	0.10	0.30	0.09	0.54
Furniture	0.17	0.40	0.15	0.86	0.09	0.37	0.19	0.44
Other manufacturing	0.21	0.45	0.27	0.64	0.14	0.40	0.11	0.51
Average	0.19	0.41	0.18	0.66	0.14	0.39	0.15	0.51
Median	0.18	0.41	0.17	0.65	0.14	0.40	0.14	0.52

S^2 and R^2 after random effects estimation of Eq. (7)

Table 7 Productivity–growth relationship, rank correlations of S^2 across countries

	France	Germany	UK	USA
France	1.00	0.13	0.74	0.15
		(0.55)	(0.00)	(0.49)
Germany		1.00	−0.04	0.35
			(0.87)	(0.10)
UK			1.00	−0.12
				(0.57)
USA				1.0

Spearman's rank correlation of the country distribution of sectoral S^2, after random effects estimation of Eq. (7). Significance levels in parenthesis

for this evidence is that the actual drivers of firm growth do not rest in the relative *levels* of productivity at any time period, but rather in their *variation* through time. We therefore need to specify a different regression model allowing to test the importance of relative productivity levels vis-à-vis relative productivity changes. The aim is to separate the S^2 obtained above from the regression Eq. (7) into a "level" component and a "dynamic" component. Accordingly, we first rewrite Eq. (6) as

$$g_{i,t} = a + b_t + \beta_\Delta \Delta\pi_{i,t} + \beta_m \bar{\pi}_{i,t} + u_i + \epsilon_{i,t} \qquad (10)$$

where $\Delta\pi_{i,t}$ is the log difference of relative productivity over two consecutive years, accounting for the *dynamics* of differential efficiency, while $\bar{\pi}_{i,t}$ is the within-firm average productivity level computed over t and $t-1$, in turn capturing the absolute differential efficiency among firms.

Next, we again resort to correlated random effects to estimate the main coefficients β_Δ and β_m. That is, we apply the random effects estimator to the regression

Table 8 Productivity levels vs. productivity changes, decomposition of S^2

	France		Germany		UK		USA	
	$S^2_{\bar{\pi}_{i,t}}$	$S^2_{\Delta\pi_{i,t}}$	$S^2_{\bar{\pi}_{i,t}}$	$S^2_{\Delta\pi_{i,t}}$	$S^2_{\bar{\pi}_{i,t}}$	$S^2_{\Delta\pi_{i,t}}$	$S^2_{\bar{\pi}_{i,t}}$	$S^2_{\Delta\pi_{i,t}}$
Food	0.00	0.14	0.00	0.17	0.00	0.09	0.01	0.03
Beverages	0.01	0.14	0.05	0.18	0.02	0.07	0.01	0.18
Textile	0.01	0.22	0.05	0.08	0.07	0.18	0.01	0.03
Wearing	0.01	0.17	0.02	0.04	0.01	0.15	0.02	0.04
Leather	0.00	0.32	0.02	0.36	0.03	0.17	0.05	0.27
Wood	0.00	0.22	0.00	0.26	0.01	0.16	0.06	0.19
Paper	0.00	0.07	0.01	0.27	0.01	0.10	0.01	0.14
Printing	0.00	0.18	0.01	0.02	0.00	0.15	0.11	0.02
Coke and petroleum	0.01	0.03	0.03	0.43	0.01	0.04	0.03	0.16
Chemical	0.00	0.10	0.00	0.16	0.00	0.06	0.02	0.08
Pharmaceutical	0.00	0.26	0.02	0.30	0.00	0.14	0.02	0.16
Rubber and plastic	0.01	0.11	0.00	0.05	0.01	0.10	0.02	0.17
Other non-metallic	0.00	0.24	0.00	0.26	0.02	0.17	0.03	0.07
Basic metals	0.00	0.22	0.02	0.15	0.00	0.21	0.02	0.09
Fabricated metal	0.01	0.23	0.00	0.18	0.01	0.12	0.03	0.25
Machinery	0.00	0.24	0.01	0.11	0.01	0.12	0.01	0.18
Computer and electronic	0.00	0.19	0.00	0.04	0.01	0.12	0.02	0.15
Electrical	0.01	0.25	0.00	0.14	0.00	0.14	0.02	0.07
Motor vehicles	0.00	0.17	0.02	0.10	0.01	0.13	0.01	0.04
Other transport	0.00	0.16	0.02	0.05	0.01	0.09	0.03	0.06
Furniture	0.02	0.15	0.01	0.15	0.02	0.08	0.06	0.13
Other manufacturing	0.01	0.20	0.02	0.25	0.01	0.14	0.00	0.11
Average	0.00	0.18	0.01	0.17	0.01	0.12	0.03	0.12
Median	0.00	0.18	0.01	0.15	0.01	0.12	0.02	0.12

$S^2_{\Delta\pi_{i,t}}$ and $S^2_{\bar{\pi}_{i,t}}$ after random effects estimation of Eq. (11)

$$g_{i,t} = a + b_t + \beta_\Delta \Delta\pi_{i,t} + \beta_m \bar{\pi}_{i,t} + \beta_{\Delta a}\bar{\Delta\pi}_i + \beta_{ma}\bar{\bar{\pi}}_i + c_i + \epsilon_{i,t}, \quad (11)$$

where we add the average of the dynamic component, $\bar{\Delta\pi}_i$, and the average of the level component, $\bar{\bar{\pi}}_i$.

We focus the discussion on the explanatory power of productivity variables. We compute the explanatory power of $\bar{\pi}_{i,t}$ and $\Delta\pi_{i,t}$ via the S^2 associated with each of the two variables, according to the formula in (8), properly modified. Under the hypothesis that firms are selected and grow mostly according to their "static" relative efficiency, one should expect the explanatory power of $\bar{\pi}_{i,t}$ to be greater than that of $\Delta\pi_{i,t}$. On the contrary, if firms are competitively rewarded mainly because of their differential productivity growth, the explanatory power of $\Delta\pi_{i,t}$ should dominate.

Results are reported in Table 8, while a graphical representation is presented in Fig. 3.[17] In nearly all sectors, and irrespective of the country considered, we find that the fraction of sales growth variance accounted for by the levels component, $S^2_{\bar{\pi}_{i,t}}$, is very close to 0. Correspondingly, the explanatory power of the dynamic component, $S^2_{\Delta\pi_{i,t}}$, is almost identical to the overall S^2 reported in Table 6. This implies that the bulk of the impact of productivity variables relates to efficiency changes more than to absolute differences of productivity levels across firms. As already noted in

[17] For completeness, Table 12 in Appendix 1 shows corresponding coefficient estimates. Notice that β_Δ and β_m are related to the coefficients of Eqs. (6) and (7) through $\beta_0 = \frac{\beta_m}{2} + \beta_\Delta$ and $\beta_1 = \frac{\beta_m}{2} - \beta_\Delta$.

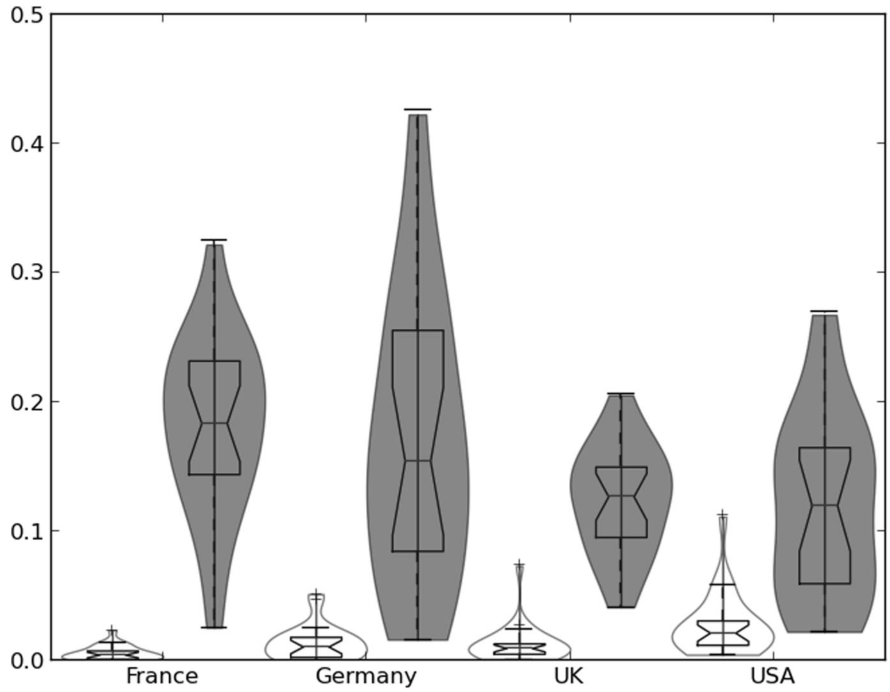


Fig. 3 Distributions of sectoral $S^2_{\Delta\pi_{i,t}}$ (*white* violins) and $S^2_{\bar{\pi}_{i,t}}$ (*shaded* violins) after random effects estimation of Eq. (11), by country. Distributions, median values, and interquartile ranges are computed according to Table 12 (see Appendix 8)

the above exercises, it is difficult to find sector-specific or country-specific patterns. If anything, the dynamic component provides a slightly larger contribution in Germany and France, at least according to median values across sectors.

The predominance of the dynamic structure also reconciles the regression analysis with the decomposition exercise, explaining why the between term of productivity decomposition did not signal any relevant selection effect at work. Indeed, we find here that the effect of reallocation and market selection among firms can only be detected in terms of relative dynamics in efficiencies, while standard decompositions only consider static efficiency differentials. This fact notwithstanding, the overall explanatory power of productivity variables remains small, confirming our main conclusion about the apparent weakness of competitive selection.[18]

5.3 Longer-run relationship

Although correlated random effects allow to pick the contribution of average productivity terms over the sample period, an alternative way to look at the structural, longer-run relationship between growth and productivity is to investigate the link between average productivity and average growth computed over multi-year sub-periods. This also allows to smooth the impact of yearly fluctuations. With 7–8 years in the data, we divide the sample period into two sub-periods and we run the following regression

$$\bar{g}_{i,p} = a + \beta_0 \bar{\pi}_{i,p} + \beta_1 \bar{\pi}_{i,p-1} + \epsilon_{i,p}, \qquad (12)$$

where the bar indicates within-firm time series average of the variables computed over the sub-periods $p = 2007-2004$ and $p - 1 = 2003-2000$ (2003–2001 for Germany).

The question is whether we can confirm the above finding of a relatively weak explanatory power of the productivity terms. The re-formulation, however, leaves us with a cross-sectional exercise, so we cannot control for firm fixed effects and time dummies. We therefore resort to simple OLS estimates and evaluate the explanatory power of productivity by a standard R^2 (i.e. S^2 and R^2 are equivalent in this exercise).

We present results in Table 9.[19] The main finding is, once again, that relative productivity variables can only explain a relatively small proportion of growth

[18] Also in this case the main conclusions remain valid under alternative regressions using TFP in place of labour productivity (see Appendix 2).

[19] Corresponding coefficient estimates are reported, for completeness, in Table 13 in Appendix 1.

Table 9 Productivity–growth long-run relationship, R^2

	France	Germany	UK	USA
Food	0.05	0.12	0.04	0.03
Beverages	0.13	0.02	0.05	0.58
Textile	0.19	0.25	0.18	0.16
Wearing	0.13	0.36	0.11	0.10
Leather	0.31	0.90	0.21	0.08
Wood	0.11	0.15	0.14	0.07
Paper	0.09	0.20	0.13	0.39
Printing	0.09	0.02	0.14	0.22
Coke and petroleum	0.12	0.03	0.22	0.02
Chemical	0.04	0.27	0.05	0.08
Pharmaceutical	0.17	0.00	0.13	0.16
Rubber and plastic	0.06	0.18	0.08	0.22
Other non-metallic	0.12	0.06	0.18	0.05
Basic metals	0.16	0.16	0.10	0.14
Fabricated metal	0.15	0.02	0.16	0.36
Machinery	0.10	0.03	0.09	0.14
Computer and electronic	0.02	0.10	0.11	0.14
Electrical	0.09	0.05	0.04	0.19
Motor vehicles	0.03	0.04	0.02	0.04
Other transport	0.02	0.29	0.07	0.16
Furniture	0.15	0.24	0.23	0.64
Other manufacturing	0.05	0.47	0.09	0.10
Average	0.11	0.18	0.12	0.18
Median	0.10	0.14	0.11	0.14

R^2 after estimation of Eq. (12)

rates variation, irrespective of the countries. Looking at median values of the sectoral R^2, the contribution of productivity is about 10 % in France and in the UK and about 15 % in Germany and in the USA. These figures well represent the underlying sector-specific estimates, although there are cases of sectors where the explanatory power is sensibly higher, e.g. for "leather" in Germany and for "beverages" and "furniture" in the USA. Despite these single cases, it is difficult to identify robust sectoral patterns holding in the same way across the four countries. Indeed, the R^2 values obtained for each sector tend to vary across countries, and we do not see common patterns characterizing groups of sectors.

6 The specificities of SMEs

The analysis of the previous sections establishes robust statistical regularities about the dynamics of industries, directly speaking against some common wisdom (apparently naive) on the strong power of competition and market selection. A major question concerns whether selection forces operate differently on smaller businesses. Entrepreneurial and economics literature have indeed provided many pieces of evidence that SMEs follow quite different trajectories. On the one hand, SMEs can be seen as a fundamental driver of industry dynamics and employment creation (Acs and Mueller 2008) and knowledge generation (Acs and Preston 1997), thus, in a sense, also driving selection by replacing less efficient competitors. On the other hand, however, there is also a view that SMEs face various type of constraints, e.g. in terms of their difficulties to access finance (Carpenter and Petersen 2002; Bottazzi et al. 2014), to formalize and sustain innovative efforts (Ortega-Argils et al. 2009), or to access international markets (Hollenstein 2005; OECD 2009). In this respect, competitive forces can yield a much tougher selection mechanism for smaller firms, although this view needs not to be in conflict with the evidence emerging from the literature on the so-called gazelles or high-growth firms. Indeed, such few dynamic firms are typically small relative to the average size in their industry, but are the drivers of new waves of innovation and are particularly reactive to new market opportunities (see Coad et al. 2014, for a critical review).[20]

In this section, we investigate whether our main findings can be qualified with respect to firm size. We again propose two distinct exercises looking first at productivity decompositions, focusing in particular on the SMEs' contribution to the aggregate sectoral between effect, and second we turn to our main firm-level regression, which we separately estimate across small–medium and larger enterprises. As standard in many international classifications (e.g. from Eurostat), we identify SMEs as firms with <250 employees, and we thus define as large firms those with 250 employees or more.

6.1 Productivity decomposition and firm size

Consider the index of aggregate productivity of sector j, $\tilde{\Pi}_{j,t}$, defined in Eq. (2) as a weighted sum of individual firms' (labour) productivities. Suppose one

[20] Young age, together with small size, is a complementary characteristic of these firms, which we cannot unfortunately measure in our data.

Table 10 Decomposition of labour productivity growth: SMEs vs. large firms

	France					Germany				
	$WITH_{SME}$	BET_{SME}	$WITH_{large}$	BET_{large}	*COV*	$WITH_{SME}$	BET_{SME}	$WITH_{large}$	BET_{large}	COV
Food	0.403	0.020	0.860	−0.229	−0.054	0.046	−0.002	0.860	0.107	−0.011
Beverages	0.464	−0.038	0.503	0.002	0.069	0.596	0.102	−0.118	0.445	−0.025
Textile	0.623	0.400	−0.188	0.143	0.021	−0.434	0.141	1.074	0.168	0.051
Wearing	0.279	0.194	0.387	0.120	0.020	−0.171	−0.022	−3.045	4.085	0.152
Leather	0.363	0.006	0.072	0.387	0.172	1.192	0.075	−0.229	−0.044	0.005
Wood	0.820	0.087	0.112	−0.007	−0.011	0.168	−0.015	0.778	0.093	−0.025
Paper	0.255	0.012	0.645	0.161	−0.073	0.640	0.228	−0.332	0.463	−0.000
Printing	0.733	0.233	−0.084	0.100	0.019	−0.163	−0.000	1.080	0.077	0.006
Coke and petroleum	0.291	0.017	0.766	−0.011	−0.062	0.054	0.008	1.240	−0.290	−0.013
Chemical	0.147	0.046	0.715	0.117	−0.025	0.011	0.002	0.923	0.063	0.002
Pharmaceutical	0.138	−0.000	0.829	0.035	−0.002	0.004	0.001	1.412	−0.418	0.001
Rubber and plastic	0.337	0.046	0.633	−0.025	0.008	0.087	−0.018	0.989	−0.066	0.008
Other non-metallic	0.221	0.031	0.677	0.123	−0.051	0.027	0.003	0.932	0.036	0.002
Basic metals	0.172	0.011	0.744	0.088	−0.015	0.085	−0.001	0.924	0.001	−0.010
Fabricated metal	0.498	0.117	0.294	0.097	−0.007	0.257	−0.029	0.778	−0.014	0.008
Machinery	0.223	0.041	0.696	0.046	−0.007	0.182	0.009	0.806	0.006	−0.004
Computer and electronic	0.285	0.210	0.496	0.263	−0.253	0.020	0.013	1.046	−0.084	0.005
Electrical	0.175	0.057	0.951	−0.162	−0.022	0.067	0.007	1.015	−0.088	−0.001
Motor vehicles	0.036	0.002	0.899	0.076	−0.014	0.009	−0.000	1.085	−0.092	−0.003
Other transport	−0.947	−0.046	1.760	0.006	0.226	−0.024	−0.003	0.921	0.112	−0.006
Furniture	0.259	0.149	0.461	0.134	−0.004	0.038	0.013	1.062	−0.111	−0.002
Other manufacturing	0.171	0.247	0.486	0.090	0.006	−0.400	−0.255	3.212	−1.581	0.024
Average	0.270	0.084	0.578	0.071	−0.003	0.104	0.012	0.746	0.131	0.007
Median	0.269	0.044	0.639	0.089	−0.007	0.042	0.002	0.928	0.004	0.000
	UK					USA				
	$WITH_{SME}$	BET_{SME}	$WITH_{large}$	BET_{large}	COV	$WITH_{SME}$	BET_{SME}	$WITH_{large}$	BET_{large}	COV
Food	0.231	0.069	1.178	−0.457	−0.021	0.000	0.000	0.781	0.219	−0.000
Beverages	0.001	0.019	1.074	−0.112	0.018	0.010	0.008	0.617	0.362	0.002
Textile	−0.490	−0.482	2.913	−1.163	0.223	–	–	–	–	–
Wearing	0.110	0.082	0.686	0.049	0.074	−0.003	0.006	0.822	0.173	0.002
Leather	0.160	0.031	0.907	−0.116	0.019	0.005	0.022	0.711	0.272	−0.011
Wood	0.272	0.062	0.641	0.031	−0.005	–	–	–	–	–
Paper	0.189	0.008	0.786	0.029	−0.012	−0.001	0.000	1.145	−0.144	0.000
Printing	−0.045	0.252	0.745	0.052	−0.004	−0.008	0.000	0.374	0.630	0.005
Coke and petroleum	0.196	0.010	0.943	−0.071	−0.077	0.000	0.000	0.911	0.089	−0.000
Chemical	0.025	0.021	0.945	0.001	0.008	−0.003	0.004	0.871	0.129	−0.001
Pharmaceutical	0.013	−0.003	1.025	−0.020	−0.016	0.006	0.003	1.008	−0.010	−0.006
	0.107	0.058	0.693	0.151	−0.009	−0.002	0.000	1.057	−0.056	0.000

Table 10 continued

	UK					USA				
	$\mathrm{WITH_{SME}}$	$\mathrm{BET_{SME}}$	$\mathrm{WITH_{large}}$	$\mathrm{BET_{large}}$	COV	$\mathrm{WITH_{SME}}$	$\mathrm{BET_{SME}}$	$\mathrm{WITH_{large}}$	$\mathrm{BET_{large}}$	COV
Other non-metallic	0.257	0.019	0.555	0.171	−0.003	−0.004	0.000	0.937	0.068	−0.000
Basic metals	0.150	0.016	0.913	−0.080	0.000	−0.000	0.000	0.891	0.109	−0.000
Fabricated metal	0.259	0.059	0.636	0.070	−0.025	0.005	0.002	0.994	−0.001	0.001
Machinery	0.123	0.030	0.774	0.082	−0.009	−0.000	0.001	0.879	0.120	−0.000
Computer and electronic	0.273	0.216	0.215	0.262	0.034	0.004	0.011	0.700	0.291	−0.006
Electrical	0.212	0.049	0.713	−0.012	0.038	0.000	0.001	1.010	−0.010	−0.001
Motor vehicles	0.066	0.012	0.896	0.024	0.001	0.000	0.000	0.950	0.050	−0.001
Other transport	0.029	0.008	0.941	0.023	−0.000	0.003	−0.001	1.004	−0.004	−0.002
Furniture	0.454	0.089	0.402	0.059	−0.003	–	–	–	–	–
Other manufacturing	0.345	0.146	0.514	−0.009	0.004	0.012	0.003	0.845	0.138	0.001
Average	0.134	0.035	0.868	−0.047	0.011	0.001	0.003	0.869	0.128	−0.001
Median	0.155	0.031	0.780	0.023	−0.001	0.000	0.001	0.891	0.109	−0.000

Decomposition as from Eq. (15), over the period from 2007 to 2000 (2001 for Germany). For each country, we report the within (WITH) and between (BET) effects for two size classes of small–medium (SME, below 250 employees) and larger (large) firms, and the interclass covariance term (COV). Values are normalized as share of aggregate sectoral productivity change. We mark with "–" the sectors where too few observations are available to compute the decomposition

wants to break it down to account for the relative contribution of k different classes of firm size. One can rewrite (omitting the j and t subscript for simplicity)

$$\tilde{\Pi} = \sum_{k=1}^{K} s_k \tilde{\Pi}_k = \sum_{k=1}^{K} s_k \sum_{i \in k} s_i \pi_i, \tag{13}$$

where $\tilde{\Pi}_k$ is the total productivity of the size category k and s_k the employment share of category k in sector j, while π_i and s_i are, respectively, the labour productivity and the employment share of firm i within the size class k the same firm belongs to.

A general decomposition of the index in terms of within and between components is as follows

$$\Delta\tilde{\Pi}_j = \sum_{k=1}^{K} s_k \sum_{i \in k} \bar{s}_i \Delta\pi_i + \sum_{k=1}^{K} s_k \sum_{i \in k} \Delta s_i \bar{\pi}_i + \sum_{k=1}^{K} \Delta s_k \bar{\tilde{\Pi}}_k, \tag{14}$$

where a bar above a variable indicates the time series average of that variable computed over two consecutive years. The first and second terms represent, respectively, the weighted sum of the within and the between effects accruing to each size class. The last term captures the contribution stemming from reallocation of shares across different size categories.

In our case, we divide firms in each sector into just two size classes, comparing SMEs vs. large firms. The formula simplifies as the sum of five terms

$$\begin{aligned}\Delta\tilde{\Pi} = {} & s_{\mathrm{SME}} \sum_{i \in \mathrm{SME}} \bar{s}_i \Delta\pi_i + s_{\mathrm{SME}} \sum_{i \in \mathrm{SME}} \Delta s_i \bar{\pi}_i \\ & + s_{\mathrm{large}} \sum_{i \in \mathrm{large}} \bar{s}_i \Delta\pi_i + s_{\mathrm{large}} \sum_{i \in \mathrm{large}} \Delta s_i \bar{\pi}_i \\ & + \sum_{k \in \{\mathrm{SME,large}\}} \Delta s_k \bar{\tilde{\Pi}}_k.\end{aligned} \tag{15}$$

The first and second terms capture the within and between components due to SMEs, while the third and fourth terms correspond to within and between components due to large firms. The last term is a "covariance term" ensuring equality and measures the dynamics of shares and productivity between the two size classes.

Table 10 presents the values of the different components, across sectors and countries. There is considerable variability, but we can nevertheless confirm a clear predominance of the within component over the between effect. In accordance with the above aggregate analysis, innovation and learning prevail over reallocation/selection forces as drivers of sectoral productivity dynamics. The result holds in basically all sectors and in all countries, and it is replicated within both SMEs and larger firms. However, we find that larger firms prominently contribute to such learning processes. Indeed, the within component associated with large firms is larger than the within effect due to SMEs in the vast majority of sectors, irrespective of the country considered. Looking at the median values, the within component of large firms is 0.639 in France, 0.928 in Germany, 0.78 in the UK, and 0.891 in the USA.

The evidence on the role of firm size in explaining our general finding of weak selection is more nuanced. Taking the median values of the between components, we observe that $\mathrm{BET}_{\mathrm{large}}$ is bigger than $\mathrm{BET}_{\mathrm{SME}}$ in France, Germany and the USA (not in the UK). However, there is also large variation at sectoral level, and we observe many instances where the between component due to small firms is larger. This pattern gives a first hint that selection and competition may bite more on smaller firms. A more precise evaluation of the importance of selection among small and large firms is gained by considering the ratio of BET over (WITH + BET) within the two size classes. The overall contribution of small firms to aggregate productivity growth $(\mathrm{WITH}_{\mathrm{SME}} + \mathrm{BET}_{\mathrm{SME}})$ is lower than the one associated with large firms in almost every country–sector pair. But, at the same time, the between component BET_{SME} represents a larger share in the total contribution of SMEs, while the opposite holds for larger firms. For example, in the chemical sector in France, while both the within and the between components of SMEs are smaller than the corresponding values of large firms, the ratio of $\mathrm{BET}_{\mathrm{SME}}$ over the total $(\mathrm{WITH}_{\mathrm{SME}} + \mathrm{BET}_{\mathrm{SME}})$ is 0.2, whereas the same ratio among large firms is 0.14. And the result is quite general: considering the sectors in which there is a positive contribution to productivity growth from both small and large firms, the relative importance of the between component is higher among SMEs firms in 11 out of 20 sectors in France, in 9 out of 16 in Germany, in 18 out of 20 in the UK, and in 10 out of 11 in the USA.

6.2 The micro-analysis conditional on firm size

We next explore whether disaggregating the samples by SMEs and larger firms improves the understanding of the overall weak power of productivity in explaining firm growth. We estimate separately by the two size classes our baseline correlated random effect specification presented in Eq. (7), and we next compute the associated S^2, giving the fraction of the overall variance of firm growth rates explained by the productivity terms.

Table 11 presents the S^2 and R^2 obtained within the two groups of small–medium versus large firms.[21] The first general conclusion is that we can confirm the aggregate finding that productivity explains, in general, a little fraction of firm growth variability. Considering the median values of the distribution of sectoral S^2, the explained variance varies from 10 to 25 %, depending on the size class and country, while firm heterogeneity accounts for a much greater fraction.

Notwithstanding this general pattern, disaggregating by size does add interesting pieces of information, as there are indeed differences across SMEs and larger firms. First, comparing the median values of S^2 (in proportion of the associated total explained variance R^2), we find larger explanatory power of productivity within the SMEs in the UK and the USA, suggesting that competitive selection affects more small–medium firms in these countries. The joint reading of S^2 and R^2 reveals similar explanatory power across the two size groups in France, and it gives a stronger productivity–growth link among large firms in Germany.

However, second, the underlying sector-specific estimates display ample heterogeneities, ranging from 0.01 (for SMEs in sector "printing" in France and for SMEs in sector "motor vehicles" in the USA) to a quite high 0.83 (for US SMEs in "rubber and plastic"). Median values can therefore be misleading as each country can have its own sectoral specificities. In France, most of the sector estimates agree with the existence of a non-systematic difference across SMEs and large firms suggested by median values, although the explanatory power of productivity is larger for large firms in some cases. In the UK, sectoral patterns are broadly in line with the conclusion emerging from

[21] We do not report results for sectors wherein the number of observations was too small to obtain reliable estimates. This applies in particular when we consider the group of SMEs in the US-COMPUSTAT database.

Table 11 Productivity–growth relationship by firm size, explained variance

	France				Germany				UK				USA			
	SMEs		large		SMEs		large		SMEs		large		SMEs		large	
	S^2	R^2	S^2	R^2	S^2	R^2	S^2	R^2	S^2	R^2	S^2	R^2	S^2	R^2	S^2	R^2
Food	0.14	0.39	0.12	0.38	0.08	0.75	0.38	0.75	0.11	0.39	0.07	0.32	0.09	0.64	0.04	0.48
Beverages	0.15	0.33	0.27	0.45	0.42	0.70	0.03	0.60	0.13	0.33	0.06	0.34	0.41	0.73	0.09	0.30
Textile	0.26	0.48	0.10	0.43	0.13	0.77	0.25	0.59	0.20	0.49	0.30	0.52	–	–	0.05	0.47
Wearing	0.19	0.41	0.15	0.38	0.07	0.74	0.21	0.60	0.30	0.49	0.05	0.34	0.08	0.67	0.09	0.44
Leather	0.32	0.53	0.58	0.77	–	–	–	–	0.27	0.50	0.28	0.51	–	–	0.34	0.77
Wood	0.20	0.41	0.18	0.30	0.32	0.93	0.40	0.87	0.19	0.44	0.22	0.49	–	–	0.25	0.65
Paper	0.09	0.29	0.04	0.39	0.45	0.93	0.32	0.60	0.16	0.42	0.09	0.31	–	–	0.09	0.33
Printing	0.22	0.42	0.01	0.24	0.03	0.75	0.06	0.55	0.14	0.43	0.20	0.35	–	–	0.17	0.39
Coke and petroleum	0.06	0.32	–	–	0.51	0.93	0.50	0.58	0.08	0.40	–	–	–	–	0.05	0.47
Chemical	0.11	0.39	0.13	0.35	0.11	0.66	0.35	0.56	0.07	0.36	0.06	0.32	0.20	0.70	0.15	0.45
Pharmaceutical	0.25	0.42	0.33	0.48	0.31	0.69	0.36	0.61	0.16	0.44	0.21	0.41	0.22	0.56	0.13	0.50
Rubber and plastic	0.15	0.36	0.06	0.24	0.08	0.54	0.06	0.65	0.11	0.37	0.14	0.36	0.83	0.92	0.11	0.42
Other non-metallic	0.25	0.47	0.21	0.47	0.13	0.67	0.46	0.71	0.22	0.47	0.18	0.40	0.40	0.70	0.06	0.41
Basic metals	0.19	0.46	0.31	0.47	0.11	0.76	0.24	0.52	0.23	0.44	0.16	0.37	–	–	0.10	0.57
Fabricated metal	0.27	0.47	0.17	0.36	0.20	0.73	0.38	0.64	0.16	0.39	0.16	0.40	0.50	0.84	0.17	0.54
Machinery	0.27	0.44	0.14	0.36	0.13	0.63	0.14	0.48	0.15	0.36	0.08	0.32	0.17	0.52	0.27	0.51
Computer and electronic	0.23	0.50	0.22	0.44	0.02	0.64	0.16	0.55	0.16	0.43	0.09	0.33	0.20	0.58	0.16	0.50
Electrical	0.26	0.44	0.29	0.47	0.19	0.62	0.19	0.53	0.18	0.42	0.09	0.29	0.07	0.47	0.13	0.45
Motor vehicles	0.20	0.39	0.18	0.49	0.23	0.72	0.06	0.47	0.19	0.44	0.09	0.34	0.01	0.32	0.16	0.41
Other transport	0.22	0.48	0.08	0.30	0.24	0.89	0.05	0.34	0.13	0.32	0.06	0.30	0.19	0.70	0.10	0.33
Furniture	0.17	0.40	0.31	0.44	0.13	0.90	0.39	0.77	0.12	0.43	0.03	0.35	–	–	0.20	0.48
Other manufacturing	0.19	0.46	0.42	0.54	0.35	0.74	0.15	0.52	0.17	0.41	0.07	0.43	0.16	0.45	0.20	0.55
Average	0.20	0.42	0.21	0.42	0.20	0.76	0.24	0.60	0.17	0.42	0.13	0.37	0.25	0.63	0.14	0.47
Median	0.20	0.42	0.18	0.43	0.13	0.74	0.24	0.59	0.16	0.43	0.09	0.35	0.19	0.66	0.13	0.47

S^2 and R^2 from random effects estimation of Eq. (7) separately by small–medium firms (SMEs, below 250 employees) and larger (large) firms. We mark with "–" the cases where too few observations are available to provide estimates

median values that selection bites more on smaller than on large firms. And the same holds for the USA, despite the above-mentioned very high pick in the S^2 of SMEs (0.83) in "rubber and plastic". In Germany, the S^2 values are more dispersed around the median than in other countries. For SMEs, the values pick in such diverse industries as "paper" (0.45), "coke and petroleum" (0.51), and "beverages" (0.42), while among large firms selection is strong in "coke and petroleum" (0.50) and in "other non-metallic" (0.46), but also in "chemicals", "pharma", and "fabricated metals" (all with S^2 above 0.35). These latter sectors drive the aggregate evidence that selection is fiercer among large firms in this country, while in the majority of other sectors we observe that competitive selection is stronger for SMEs even in this country.

To sum up, both the productivity decomposition and the regression analysis reveal significant differences between SMEs and larger firms, both in the smaller contribution of the former to learning dynamics and in the larger effectiveness of selection mechanisms among SMEs.

7 Conclusions

This paper contributes to the analysis of the workings of market selection and reallocation in four different countries, characterized by different institutional set-ups.

The first exercise proposed here supports those previous studies claiming that productivity growth is, for the most part, the result of a process of learning which takes place within the firms. Indeed, in a decomposition of sectoral productivity growth, the small relative magnitude of the between component as compared to the within one points in the direction of a weak contribution to the dynamics of aggregate industry productivity of the reallocation of market shares.

We next search more directly for the fingerprints of competitive selection, by estimating the micro-relationships between relative efficiency levels and relative growth rates. The findings confirm that the power of selection mechanisms is modest, although somewhat stronger as compared to the decomposition exercise. The explanatory power associated with productivity variables ranges from one-fifth to one-sixth of the overall variance of firm growth rates. At the same time, this explanatory power entirely rests on the *changes* over time in relative productivities, that is on the rates of relative productivity *growth*, while relative efficiency levels hardly seem to contribute.

All this evidence does anything but reinforce the view that no naive form of competitive process primarily driven by relative productive efficiencies is effectively at work. Moreover, the significant role played by *relative changes* in productivities, rather than *relative levels* goes against the prediction of most models of selection and industry dynamics, both of the "disequilibrium" type as in Nelson and Winter (1982) and Dosi et al. (1995), and equilibrium ones *à la* Jovanovic (1982).

How do we interpret all this? First, an important qualification of the results comes from our analysis of the role of firm size. We indeed find that both within SMEs and within large firms selection forces are comparatively less important than learning and innovation as drivers of sectoral productivity, but such improvements (or losses) in within-firm productivity originate primarily from the group of larger firms, thus echoing the so-called Schumpeter Mark II hypothesis about the central role of large firms in innovative activity of sectors. Moreover, regression analysis suggests that selection, although weak, is relatively fiercer for SMEs than for larger firms.

Second, the importance of unobserved firm-specific determinants of corporate growth plausibly hints at finer characteristics of products and of firm strategies not captured by industry-wide proxies for production efficiency. Third, regarding the (smaller but sizable) role of *changes* in relative productivities, our conjecture, which can be in principle tested over more disaggregated product-level data, is the following. Suppose every 2-digit (but also 3- and 4-digit) industry is composed of several sub-markets of different size, in tune with Sutton (1998), which are also the *loci* of competition (see also Dosi et al. 2013). So, for example, the car industry is composed of different segments, whereby Fiat 500 does not compete with Audi A4 which does not compete with Ferrari. Think of this example in terms of the "fitness landscape" representation quite common in the organization literature, linking some organizational trait (say, productivity, Π) to some measure of fitness (f) of the organization, like in Fig. 4. Here, there are three "submarkets" with three different "peaks" in the relationship productivity–fitness. And of course each sub-market is characterized by different average productivities, in addition to obvious differences in product characteristics. In each of the submarkets, it is plausible to think of a relation relative productivity–relative fitness–relative growth of a sort of replicator type. However, what one does in the estimates above is

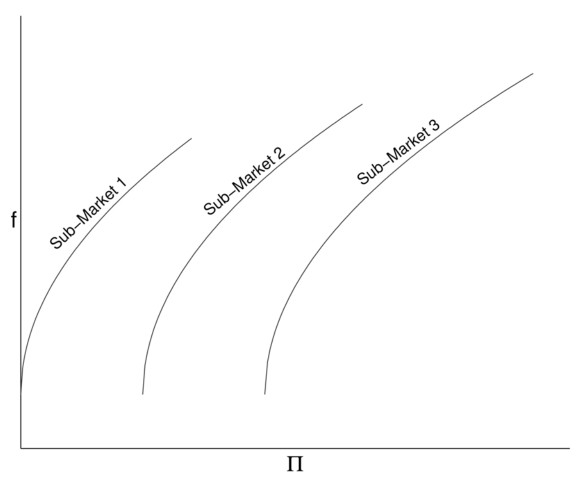


Fig. 4 Submarkets landscape

to compare the productivities of *all* firms in the industries—Fiat, Audi, Ferrari...—and not surprisingly all replicator-type properties disappear. At the same time, though, within each submarket any improvement in productivity yields, other things being equal, an improvement in fitness. And this is precisely what relative rates of productivity growth noisily capture.

This interpretation of course does not rule out the widespread possibility, already flagged in Bottazzi et al. (2010), that the relationship between efficiency and growth is deeply shaped by behavioural factors—such as the "satisfying" aspirations of the various firms, their internal structure and in particular financial conditions, together with other dimensions idiosyncratic to each firm, implying that corporate growth is heavily driven by idiosyncratic and slowly changing configurations of characteristics (knowledge bases, routines, cultures). Such corporate identities ought to be considered in the short term more as state variables rather than control variables, as Winter (1987) puts it, subject to full strategic discretionality or, even less, to passive adaptation to market conditions. The evidence is in tune with capability-based or resource-based theories of the firm. The interpretation is in principle testable, but requires much finer evidence on behavioural patterns and organizational structures.

Acknowledgments We thank Davide Castellani, Davide Fiaschi, Daniel Levinthal, Bart Verspagen, and Jeffrey Wooldridge for insightful comments. We also thank participants to the DRUID Academy Conference in Cambridge (2012), the CCC Colloquium for Doctoral Student Research in Maryland (2012), the DRUID Celebration Conference in Barcelona (2013), and the 8th EMAEE Conference in Nice (2013). The usual disclaimer applies.

Appendix 1: complementary tables

See Tables 12 and 13.

Table 12 Productivity levels versus productivity changes, coefficients

	France		Germany		UK		USA	
	β_m	β_Δ	β_m	β_Δ	β_m	β_Δ	β_m	β_Δ
Food	0.020*	0.210***	−0.076	0.309***	0.012	0.174***	0.061	0.155***
	(0.011)	(0.007)	(0.054)	(0.029)	(0.018)	(0.011)	(0.047)	(0.034)
Beverages	0.070***	0.172***	−0.268***	0.301***	0.141***	0.180***	0.026	0.279***
	(0.024)	(0.014)	(0.088)	(0.050)	(0.035)	(0.023)	(0.071)	(0.061)
Textile	0.002	0.284***	0.018	0.256***	0.044**	0.146***	0.079	0.248**
	(0.017)	(0.011)	(0.135)	(0.067)	(0.020)	(0.011)	(0.159)	(0.119)
Wearing	0.053***	0.219***	−0.156*	0.117**	0.068***	0.178***	0.034	0.130***
	(0.020)	(0.013)	(0.085)	(0.052)	(0.027)	(0.019)	(0.041)	(0.027)
Leather	0.012	0.381***	0.047	0.355***	0.090*	0.151***	0.103*	0.402***
	(0.029)	(0.021)	(0.045)	(0.046)	(0.052)	(0.034)	(0.061)	(0.052)
Wood	0.025	0.267***	0.112	0.488***	−0.032	0.181***	−0.018	0.201***
	(0.016)	(0.010)	(0.129)	(0.068)	(0.028)	(0.017)	(0.057)	(0.036)
Paper	−0.012	0.113***	0.165***	0.336***	0.032	0.100***	0.013	0.279***
	(0.017)	(0.010)	(0.060)	(0.033)	(0.021)	(0.012)	(0.071)	(0.051)
Printing	0.052***	0.219***	0.149	0.136**	0.011	0.220***	−0.410***	0.112*
	(0.019)	(0.010)	(0.102)	(0.068)	(0.021)	(0.012)	(0.118)	(0.065)
Coke and petroleum	0.031	−0.015	−0.092	0.510***	−0.025	0.115***	−0.145**	−0.004
	(0.053)	(0.032)	(0.122)	(0.093)	(0.062)	(0.041)	(0.066)	(0.050)
Chemical	−0.007	0.154***	0.022	0.184***	0.030**	0.097***	−0.053*	0.181***
	(0.015)	(0.009)	(0.041)	(0.020)	(0.014)	(0.008)	(0.029)	(0.021)
Pharmaceutical	0.043	0.324***	0.109**	0.205***	0.068**	0.159***	0.005	0.250***
	(0.031)	(0.021)	(0.050)	(0.024)	(0.029)	(0.016)	(0.030)	(0.019)

Table 12 continued

	France		Germany		UK		USA	
	β_m	β_Δ	β_m	β_Δ	β_m	β_Δ	β_m	β_Δ
Rubber and plastic	−0.022	0.210***	−0.027	0.147***	0.016	0.172***	0.024	0.153***
	(0.015)	(0.009)	(0.060)	(0.029)	(0.020)	(0.012)	(0.070)	(0.032)
Other non-metallic	−0.006	0.259***	0.077	0.407***	−0.025	0.215***	−0.123*	0.198***
	(0.017)	(0.011)	(0.074)	(0.034)	(0.021)	(0.014)	(0.064)	(0.053)
Basic metals	−0.015	0.249***	0.065	0.200***	0.006	0.258***	−0.021	0.149***
	(0.021)	(0.012)	(0.040)	(0.027)	(0.028)	(0.018)	(0.053)	(0.035)
Fabricated metal	0.037***	0.361***	−0.072*	0.236***	0.021	0.223***	0.152***	0.305***
	(0.010)	(0.006)	(0.043)	(0.023)	(0.015)	(0.008)	(0.052)	(0.029)
Machinery	0.056***	0.322***	0.098***	0.248***	0.038**	0.171***	−0.006	0.219***
	(0.015)	(0.008)	(0.036)	(0.018)	(0.016)	(0.009)	(0.024)	(0.014)
Computer and electronic	0.011	0.244***	−0.073	0.203***	0.022	0.189***	0.095***	0.201***
	(0.021)	(0.012)	(0.055)	(0.030)	(0.014)	(0.008)	(0.013)	(0.007)
Electrical	−0.098***	0.351***	0.082*	0.229***	0.007	0.207***	0.172***	0.237***
	(0.024)	(0.014)	(0.043)	(0.028)	(0.019)	(0.011)	(0.053)	(0.035)
Motor vehicles	−0.031	0.257***	−0.107*	0.186***	−0.084***	0.178***	0.101	0.254***
	(0.026)	(0.015)	(0.061)	(0.035)	(0.029)	(0.017)	(0.091)	(0.058)
Other transport	−0.043	0.261***	0.114	0.279**	0.047	0.131***	−0.003	0.287***
	(0.037)	(0.023)	(0.197)	(0.112)	(0.029)	(0.014)	(0.075)	(0.052)
Furniture	0.019	0.210***	0.005	0.632***	0.100***	0.173***	0.229***	0.200***
	(0.029)	(0.013)	(0.137)	(0.082)	(0.032)	(0.018)	(0.078)	(0.048)
Other manufacturing	0.059**	0.347***	−0.060	0.240***	−0.005	0.202***	0.040	0.157***
	(0.027)	(0.017)	(0.066)	(0.038)	(0.016)	(0.009)	(0.029)	(0.018)

Random effects estimates of Eq. (11), robust standard errors in parenthesis

*** $p<0.01$, ** $p<0.05$, * $p<0.10$

Table 13 Productivity–growth long-term relationship, coefficients

	France		Germany		UK		USA	
	β_0	β_1	β_0	β_1	β_0	β_1	β_0	β_1
Food	0.110***	−0.095***	0.141***	−0.129***	0.116***	−0.106***	0.093	−0.090
	(0.012)	(0.011)	(0.040)	(0.039)	(0.025)	(0.026)	(0.057)	(0.057)
Beverages	0.087***	−0.051***	−0.051	0.056	0.106**	−0.045	0.380***	−0.472***
	(0.019)	(0.019)	(0.065)	(0.068)	(0.049)	(0.050)	(0.070)	(0.071)
Textile	0.172***	−0.104***	0.206**	−0.085	0.156***	−0.118***	0.299	−0.425
	(0.017)	(0.020)	(0.084)	(0.084)	(0.023)	(0.030)	(0.196)	(0.303)
Wearing	0.107***	−0.104***	−0.081	0.176***	0.105***	−0.093***	0.104**	−0.047
	(0.015)	(0.017)	(0.051)	(0.062)	(0.027)	(0.026)	(0.044)	(0.040)
Leather	0.230***	−0.175***	0.015	−0.218	0.110	0.184	0.053	−0.001
	(0.028)	(0.031)	(0.140)	(0.075)	(0.087)	(0.116)	(0.058)	(0.061)
Wood	0.152***	−0.111***	0.203	−0.122	0.148***	−0.118***	0.011	0.065
	(0.018)	(0.018)	(0.118)	(0.148)	(0.032)	(0.031)	(0.106)	(0.121)
Paper	0.091***	−0.073***	0.133***	−0.127***	0.116***	−0.056**	0.373***	−0.375***
	(0.015)	(0.017)	(0.041)	(0.039)	(0.021)	(0.028)	(0.071)	(0.067)

Table 13 continued

	France		Germany		UK		USA	
	β_0	β_1	β_0	β_1	β_0	β_1	β_0	β_1
Printing	0.183***	−0.162***	−0.000	0.035	0.184***	−0.211***	0.361	0.001
	(0.025)	(0.025)	(0.053)	(0.063)	(0.027)	(0.026)	(0.263)	(0.150)
Coke and petroleum	0.081	−0.050	0.020	−0.016	0.236**	−0.157	0.042	−0.031
	(0.051)	(0.051)	(0.046)	(0.112)	(0.111)	(0.151)	(0.062)	(0.068)
Chemical	0.066***	−0.052***	0.120***	−0.172***	0.090***	−0.071***	−0.011	0.094**
	(0.014)	(0.013)	(0.026)	(0.027)	(0.017)	(0.021)	(0.027)	(0.039)
Pharmaceutical	0.139***	−0.110***	0.002	−0.015	0.158***	−0.055	0.121***	−0.066***
	(0.025)	(0.026)	(0.073)	(0.074)	(0.039)	(0.037)	(0.022)	(0.024)
Rubber and plastic	0.109***	−0.051***	0.120***	−0.170***	0.125***	−0.080***	0.112	0.110
	(0.014)	(0.012)	(0.034)	(0.046)	(0.020)	(0.018)	(0.091)	(0.092)
Other non-metallic	0.153***	−0.117***	0.045	−0.082*	0.145***	−0.073***	0.071	−0.030
	(0.018)	(0.020)	(0.050)	(0.044)	(0.022)	(0.027)	(0.069)	(0.081)
Basic metals	0.123***	−0.062***	0.132***	−0.113***	0.156***	−0.108***	0.061	0.098*
	(0.017)	(0.019)	(0.034)	(0.039)	(0.032)	(0.035)	(0.045)	(0.050)
Fabricated metal	0.208***	−0.163***	0.053	−0.020	0.214***	−0.155***	0.388***	−0.424***
	(0.010)	(0.011)	(0.032)	(0.029)	(0.016)	(0.019)	(0.062)	(0.068)
Machinery	0.167***	−0.133***	0.066***	−0.016	0.110***	−0.056***	0.103***	−0.042*
	(0.016)	(0.016)	(0.024)	(0.017)	(0.015)	(0.017)	(0.018)	(0.022)
Computer and electronic	0.021	−0.059***	0.037	−0.123***	0.107***	−0.067***	0.135***	−0.082***
	(0.019)	(0.019)	(0.048)	(0.036)	(0.012)	(0.014)	(0.013)	(0.013)
Electrical	0.140***	−0.077***	0.074*	−0.077**	0.099***	−0.063***	0.182***	−0.123***
	(0.022)	(0.023)	(0.038)	(0.032)	(0.021)	(0.024)	(0.042)	(0.043)
Motor vehicles	0.107***	−0.048*	0.083	−0.032	0.041	−0.064*	0.076	−0.099*
	(0.031)	(0.028)	(0.057)	(0.050)	(0.037)	(0.036)	(0.060)	(0.056)
Other transport	0.064	−0.070*	−0.486**	0.135	0.092***	−0.091***	0.113	−0.279**
	(0.040)	(0.039)	(0.217)	(0.253)	(0.030)	(0.027)	(0.105)	(0.107)
Furniture	0.171***	−0.059**	0.126	0.034	0.189***	−0.117***	0.269***	−0.175***
	(0.024)	(0.026)	(0.088)	(0.099)	(0.027)	(0.029)	(0.044)	(0.047)
Other manufacturing	0.118***	−0.088**	0.249***	−0.189***	0.157***	−0.107***	0.106***	−0.115***
	(0.029)	(0.034)	(0.044)	(0.044)	(0.021)	(0.024)	(0.029)	(0.033)

OLS estimates of Eq. (12), robust standard errors in parenthesis

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Appendix 2: robustness checks with TFP

We provide here a robustness analysis of our main results from firm-level regressions with respect to a TFP measure of productivity. This is obtained via estimating a simple production function

$$y_{i,t} = \beta_0 + \beta_l l_{i,t} + \beta_k k_{i,t} + e_{i,t} \tag{16}$$

where $y_{i,t}$ is the (log) real sales of firm i, $l_{i,t}$ the (log) number of employees, and $k_{i,t}$ the (log) real tangible assets. We estimate Eq. (16) separately by 2-digit sectors. We unfortunately lack data on materials needed to apply Levinsohn–Petrin or similar methods. [22]

[22] However, Van Beveren (2012) shows that the "simple" TFP measure is highly correlated with the TFP derived from more sophisticated estimators: in his data, the TFP obtained through the Levinsohn–Petrin estimation algorithm has a 0.9262 correlation with the OLS measure.

Table 14 TFP–growth relationship, coefficients

	France		Germany		UK		USA	
	β_0	β_1	β_0	β_1	β_0	β_1	β_0	β_1
Food	1.485***	−1.530***	2.126***	−1.562***	0.805***	−0.753***	0.198**	−0.392***
	(0.043)	(0.042)	(0.290)	(0.289)	(0.069)	(0.067)	(0.080)	(0.083)
Beverages	1.589***	−0.917***	0.442	−1.291***	−0.033	−0.673***	0.121	0.083
	(0.117)	(0.090)	(0.277)	(0.240)	(0.052)	(0.130)	(0.134)	(0.135)
Textile	1.297***	−1.150***	0.639	−0.696	0.858***	−0.799***	0.303	−0.037
	(0.053)	(0.053)	(0.441)	(0.446)	(0.084)	(0.083)	(0.250)	(0.268)
Wearing	0.877***	−0.603***	0.484	−1.311***	0.972***	−0.496***	0.532***	−0.624***
	(0.058)	(0.057)	(0.392)	(0.357)	(0.140)	(0.137)	(0.119)	(0.115)
Leather	1.288***	−1.226***	0.887	−0.183	0.223*	−0.386***	0.392***	−0.436***
	(0.068)	(0.062)	(0.642)	(0.448)	(0.122)	(0.133)	(0.144)	(0.143)
Wood	1.349***	−1.380***	2.264***	−1.720***	1.240***	−1.732***	1.140***	−1.109***
	(0.063)	(0.063)	(0.422)	(0.356)	(0.106)	(0.099)	(0.224)	(0.270)
Paper	1.035***	−0.952***	1.847***	−0.987***	0.673***	−1.317***	0.158	−0.686***
	(0.078)	(0.073)	(0.234)	(0.204)	(0.067)	(0.099)	(0.101)	(0.095)
Printing	0.827***	−0.838***	0.295	0.142	0.578***	−0.719***	−0.305	0.189
	(0.047)	(0.047)	(0.348)	(0.255)	(0.051)	(0.054)	(0.206)	(0.201)
Coke and petroleum	−0.287	0.032	1.292***	−2.021***	−0.070	−0.130	−0.472**	0.301**
	(0.412)	(0.411)	(0.291)	(0.335)	(0.290)	(0.377)	(0.196)	(0.153)
Chemical	0.848***	−0.910***	1.205***	−1.385***	0.354***	−0.156***	0.651***	−0.532***
	(0.068)	(0.070)	(0.170)	(0.167)	(0.059)	(0.058)	(0.078)	(0.069)
Pharmaceutical	1.316***	−1.312***	0.878***	−0.811***	0.377***	−0.234***	0.628***	−0.786***
	(0.121)	(0.115)	(0.189)	(0.204)	(0.081)	(0.061)	(0.060)	(0.053)
Rubber and plastic	1.315***	−1.539***	1.407***	−1.661***	1.085***	−1.434***	−0.199	0.002
	(0.050)	(0.046)	(0.209)	(0.202)	(0.054)	(0.053)	(0.187)	(0.168)
Other non-metallic	0.704***	−0.997***	1.513***	−1.464***	0.501***	−0.424***	−0.077	−0.384***
	(0.052)	(0.056)	(0.208)	(0.213)	(0.077)	(0.066)	(0.139)	(0.141)
Basic metals	1.545***	−1.704***	1.592***	−1.022***	0.663***	−0.615***	0.753***	−0.805***
	(0.073)	(0.072)	(0.232)	(0.220)	(0.115)	(0.107)	(0.148)	(0.152)
Fabricated metal	1.487***	−1.417***	1.067***	−1.240***	1.080***	−1.087***	1.256***	−0.447***
	(0.025)	(0.024)	(0.146)	(0.149)	(0.038)	(0.038)	(0.124)	(0.108)
Machinery	1.719***	−1.724***	0.749***	−0.913***	0.505***	−0.302***	1.072***	−0.769***
	(0.042)	(0.039)	(0.124)	(0.117)	(0.051)	(0.052)	(0.067)	(0.061)
Computer and electronic	0.735***	−1.003***	0.378**	−0.422***	0.692***	−0.727***	0.698***	−0.584***
	(0.057)	(0.053)	(0.156)	(0.158)	(0.039)	(0.041)	(0.030)	(0.028)
Electrical	1.472***	−1.792***	0.673***	−0.931***	1.008***	−1.078***	0.247*	−0.126
	(0.072)	(0.064)	(0.144)	(0.176)	(0.073)	(0.069)	(0.127)	(0.104)
Motor vehicles	1.463***	−1.889***	−0.473**	−0.030	1.068***	−1.730***	0.280**	−0.203*
	(0.091)	(0.097)	(0.199)	(0.203)	(0.094)	(0.093)	(0.120)	(0.120)
Other transport	0.623***	−0.644***	0.003	−0.914**	0.980***	−0.953***	0.930***	−0.547***
	(0.116)	(0.110)	(0.423)	(0.418)	(0.096)	(0.087)	(0.114)	(0.118)
Furniture	1.149***	−1.395***	0.529	−1.191*	0.767***	−0.553***	0.502***	0.201
	(0.080)	(0.076)	(0.336)	(0.649)	(0.105)	(0.114)	(0.129)	(0.153)
Other manufacturing	1.538***	−1.324***	0.681***	−1.097***	0.917***	−0.995***	0.257***	−0.222***
	(0.063)	(0.062)	(0.203)	(0.144)	(0.053)	(0.053)	(0.050)	(0.054)

Random effects estimates of Equation (7) with TFP as proxy for productivity. Standard errors in parenthesis

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 15 TFP–growth relationship, explained variance

	France		Germany		UK		USA	
	S^2	R^2	S^2	R^2	S^2	R^2	S^2	R^2
Food	0.22	0.46	0.06	0.76	0.08	0.35	0.03	0.49
Beverages	0.20	0.38	0.16	0.52	0.04	0.27	0.02	0.35
Textile	0.27	0.50	0.08	0.56	0.26	0.49	0.08	0.45
Wearing	0.13	0.39	0.07	0.70	0.10	0.35	0.15	0.58
Leather	0.44	0.63	0.18	0.90	0.20	0.44	0.14	0.63
Wood	0.25	0.44	0.39	0.88	0.36	0.55	0.19	0.64
Paper	0.16	0.35	0.38	0.72	0.15	0.47	0.13	0.42
Printing	0.20	0.42	0.01	0.66	0.07	0.41	0.05	0.23
Coke and petroleum	0.01	0.28	0.52	0.76	0.01	0.39	0.01	0.60
Chemical	0.09	0.37	0.17	0.63	0.02	0.32	0.13	0.56
Pharmaceutical	0.21	0.39	0.12	0.53	0.05	0.37	0.20	0.57
Rubber and plastic	0.27	0.46	0.15	0.58	0.25	0.50	0.04	0.46
Other non-metallic	0.17	0.44	0.18	0.63	0.07	0.37	0.04	0.46
Basic metals	0.36	0.57	0.09	0.61	0.07	0.36	0.14	0.53
Fabricated metal	0.33	0.54	0.15	0.68	0.21	0.42	0.33	0.68
Machinery	0.38	0.55	0.07	0.55	0.05	0.30	0.22	0.52
Computer and electronic	0.22	0.49	0.02	0.57	0.10	0.40	0.14	0.54
Electrical	0.32	0.51	0.06	0.50	0.14	0.38	0.01	0.36
Motor vehicles	0.26	0.47	0.15	0.62	0.26	0.53	0.02	0.37
Other transport	0.12	0.35	0.09	0.43	0.18	0.36	0.32	0.60
Furniture	0.20	0.46	0.08	0.77	0.06	0.38	0.13	0.47
Other manufacturing	0.35	0.56	0.28	0.68	0.15	0.42	0.03	0.50
Average	0.23	0.46	0.16	0.65	0.13	0.40	0.12	0.50
Median	0.22	0.46	0.14	0.63	0.10	0.39	0.13	0.51

S^2 and R^2 after random effects estimation of Eq. (7) with TFP as proxy for productivity

In Table 14, we show the coefficient estimates of our correlated random effects baseline specification

$$g_{i,t} = a + b_t + \beta_0 \mathrm{TFP}_{i,t} + \beta_1 \mathrm{TFP}_{i,t-1} + \beta_{0a} \bar{\mathrm{TFP}}_i + \beta_{1a} \bar{\mathrm{TFP}}_{i,-1} + c_i + \epsilon_{i,t}, \tag{17}$$

which is exactly Eq. (7) with TFP in place of labour productivity. The results show that our main conclusions continue to hold. Indeed, the regularity about the distributions of signs and values is still there: β_0 and β_1 are on average equal in magnitude and opposite in sign.

The corresponding values of S^2 and R^2 are presented in Table 15. We observe some increase in the explanatory power as compared to labour productivity, as we would expect given that TFP also accounts for capital intensity. However, we confirm the general result of an overall weak power of the TFP-related terms.

We also estimate the dynamic equation

$$g_{i,t} = a + b_t + \beta_\Delta \Delta TFP_{i,t} + \beta_m T\bar{F}P_{i,t} + \beta_{\Delta a} \Delta T\bar{F}P_i + \beta_{ma} T\bar{\bar{F}}P_i + c_i + \epsilon_{i,t}, \tag{18}$$

where, as in Eq. (11), we explore the relative explanatory power of levels vs. changes of TFP variable. The findings, in Table 16 and Fig. 5, confirm that the explanatory power stems from *changes* more than from *levels* of productivity itself.

Table 16 TFP–growth relationship, decomposition of S^2

	France		Germany		UK		USA	
	$S^2_{T\bar{F}P_{i,t}}$	$S^2_{\Delta TFP_{i,t}}$	$S^2_{T\bar{F}P_{i,t}}$	$S^2_{\Delta TFP_{i,t}}$	$S^2_{T\bar{F}P_{i,t}}$	$S^2_{\Delta TFP_{i,t}}$	$S^2_{T\bar{F}P_{i,t}}$	$S^2_{\Delta TFP_{i,t}}$
Food	0.00	0.22	0.00	0.06	0.00	0.08	0.00	0.03
Beverages	0.01	0.19	0.04	0.12	0.03	0.01	0.01	0.01
Textile	0.00	0.27	0.02	0.06	0.03	0.24	0.08	0.00
Wearing	0.01	0.13	0.02	0.05	0.01	0.09	0.01	0.14
Leather	0.00	0.43	0.04	0.14	0.00	0.20	0.04	0.11
Wood	0.00	0.24	0.00	0.39	0.02	0.34	0.04	0.15
Paper	0.00	0.16	0.01	0.37	0.01	0.14	0.04	0.09
Printing	0.00	0.20	0.01	0.00	0.00	0.07	0.00	0.05
Coke and petroleum	0.00	0.01	0.03	0.49	0.00	0.00	0.00	0.01
Chemical	0.00	0.09	0.00	0.16	0.00	0.02	0.02	0.11
Pharmaceutical	0.00	0.21	0.00	0.12	0.01	0.04	0.01	0.18
Rubber and plastic	0.00	0.26	0.00	0.14	0.01	0.24	0.01	0.03
Other non-metallic	0.00	0.16	0.00	0.18	0.01	0.06	0.02	0.02
Basic metals	0.00	0.36	0.01	0.08	0.01	0.06	0.05	0.09
Fabricated metal	0.00	0.32	0.00	0.14	0.01	0.20	0.03	0.30
Machinery	0.00	0.38	0.00	0.07	0.01	0.04	0.01	0.21
Computer and electronic	0.01	0.21	0.00	0.02	0.00	0.10	0.01	0.13
Electrical	0.01	0.31	0.00	0.06	0.00	0.14	0.00	0.01
Motor vehicles	0.00	0.25	0.01	0.14	0.01	0.25	0.00	0.02
Other transport	0.00	0.12	0.01	0.07	0.01	0.17	0.02	0.30
Furniture	0.01	0.19	−0.00	0.08	0.01	0.05	0.09	0.03
Other manufacturing	0.01	0.34	0.02	0.26	0.00	0.15	0.00	0.03

$S^2_{\Delta TFP_{i,t}}$ and $S^2_{T\bar{F}P_{i,t}}$ after random effects estimation of Eq. (11) with TFP as proxy for productivity

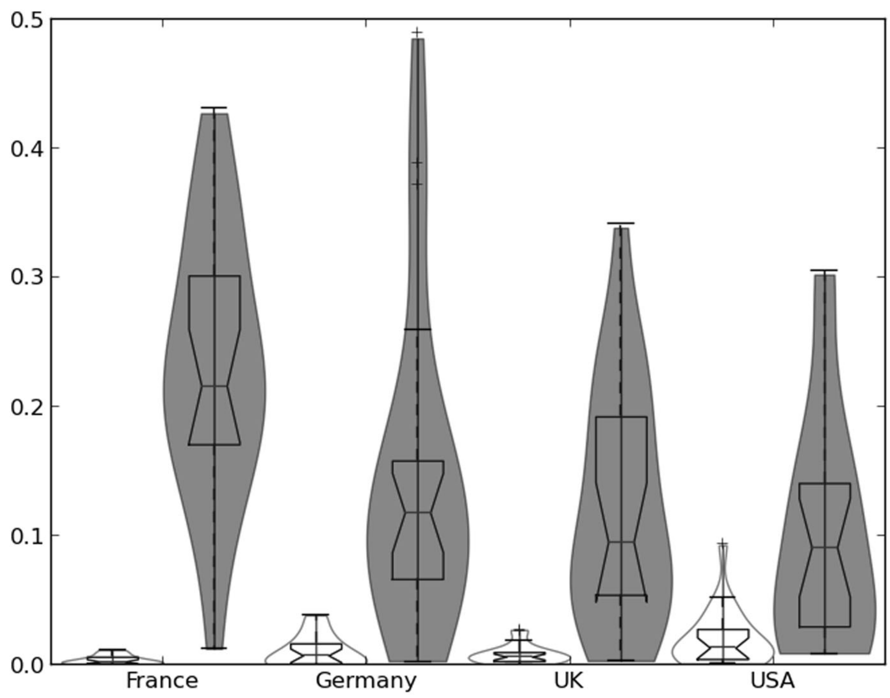


Fig. 5 Distributions by country of sectoral $S^2_{\Delta\pi_{i,t}}$ (*white* violins) and $S^2_{\bar{\pi}_{i,t}}$ (*shaded* violins) after random effects estimation of Eq. (11) with TFP as proxy for productivity. Distributions, median values, and interquartile ranges are computed according to Table 16

References

Acemoglu, D., Akcigit, U., Bloom, N., & Kerr, W. R., (2013). Innovation, reallocation and growth. NBER working paper 18993. National Bureau of Economic Research.

Acs, Z., & Mueller, P. (2008). Employment effects of business dynamics: Mice, Gazelles and Elephants. *Small Business Economics*, *30*, 85–100.

Acs, Z. J., & Preston, L. (1997). Small and medium-sized enterprises, technology, and globalization: Introduction to a special issue on small and medium-sized enterprises in the global economy. *Small Business Economics*, *9*, 1–6.

Baily, M. N., Hulten, C., & Campbell, D. (1992). Productivity dynamics in manufacturing plants. Brookings papers on economic activity. *Microeconomics*, *4*, 187–267.

Baldwin, J. R., & Gu, W. (2006). Plant turnover and productivity growth in canadian manufacturing. *Industrial and Corporate Change*, *15*, 417–465.

Bartelsman, E., Scarpetta, S., & Schivardi, F. (2005). Comparative analysis of firm demographics and survival: Evidence from micro-level sources in OECD countries. *Industrial and Corporate Change*, *14*, 365–391.

Bartelsman, E. J., & Doms, M. (2000). Understanding productivity: Lessons from longitudinal microdata. *Journal of Economic Literature*, *38*, 569–594.

Bottazzi, G., Dosi, G., Jacoby, N., Secchi, A., & Tamagni, F. (2010). Corporate performances and market selection: Some comparative evidence. *Industrial and Corporate Change*, *19*, 1953–1996.

Bottazzi, G., Dosi, G., & Rocchetti, G. (2001). Modes of knowledge accumulation, entry regimes and patterns of industrial evolution. *Industrial and Corporate Change*, *10*, 609–638.

Bottazzi, G., & Secchi, A. (2006). Explaining the distribution of firms growth rates. *The RAND Journal of Economics*, *37*, 235–256.

Bottazzi, G., Secchi, A., & Tamagni, F. (2008). Productivity, profitability and financial performance. *Industrial and Corporate Change*, *17*, 711–751.

Bottazzi, G., Secchi, A., & Tamagni, F. (2014). Financial constraints and firm dynamics. *Small Business Economics*, *42*, 99–116.

Brynjolfsson, E., & Hitt, L. M. (2003). Computing productivity: Firm-level evidence. *Review of Economics and Statistics*, *85*, 793–808.

Carpenter, R. E., & Petersen, B. C. (2002). Is the growth of small firms constrained by internal finance? *The Review of Economics and Statistics*, *84*, 298–309.

Coad, A. (2009). *The growth of firms: A survey of theories and empirical evidence*. Cheltenham: Edward Elgar.

Coad, A., Daunfeldt, S. O., Hlzl, W., Johansson, D., & Nightingale, P. (2014). High-growth firms: Introduction to the special section. *Industrial and Corporate Change*, *23*, 91–112.

Disney, R., Haskel, J., & Heden, Y. (2003). Entry, exit and establishment survival in UK manufacturing. *Journal of Industrial Economics*, *51*, 91–112.

Dosi, G. (2007). Statistical regularities in the evolution of industries. A guide through some evidence and challenges for the theory. In F. Malerba & S. Brusoni (Eds.), *Perspectives on innovation*. Cambridge, UK: Cambridge University Press.

Dosi, G., Gambardella, A., Grazzi, M., & Orsenigo, L. (2013). Technological revolutions and the evolution of industrial structures: Assessing the impact of new technologies upon the size, pattern of growth, and boundaries of firms. In G. Dosi & L. Galambos (Eds.), *The third industrial revolution in global business*. Cambridge, UK: Cambridge University Press.

Dosi, G., & Grazzi, M. (2006). Technologies as problem-solving procedures and technologies as input–output relations: Some perspectives on the theory of production. *Industrial and Corporate Change*, *15*, 173–202.

Dosi, G., Marsili, O., Orsenigo, L., & Salvatore, R. (1995). Learning, market selection and evolution of industrial structures. *Small Business Economics*, *7*, 411–436.

Ericson, R., & Pakes, A. (1995). Markov-perfect industry dynamics: A framework for empirical work. *Review of Economic Studies*, *62*, 53–82.

Foster, L., Haltiwanger, J., & Krizan, C. J. (2001). Aggregate productivity growth: Lessons from microeconomic evidence. In C. R. Hulton, E. R. Dean, & M. J. Harper (Eds.), *New Developments in Productivity Analysis* (pp. 303–363). Chicago: University of Chicago Press.

Griliches, Z., & Regev, H. (1995). Firm productivity in israeli industry 1979–1988. *Journal of Econometrics*, *65*, 175–203.

Hollenstein, H. (2005). Determinants of international activities: Are SMEs different? *Small Business Economics*, *24*, 431–450.

Hopenhayn, H. A. (1992). Entry, exit, and firm dynamics in long run equilibrium. *Econometrica*, *60*, 1127–50.

Jovanovic, B. (1982). Selection and the evolution of industry. *Econometrica*, *50*, 649–70.

Luttmer, E. G. J. (2007). Selection, growth and the size distribution of firms. *The Quarterly Journal of Economics*, *122*, 1103–1144.

Metcalfe, S. J. (1998). *Evolutionary economics and creative destruction*. London, UK: Routledge.

Mundlak, Y. (1978). On the pooling of time series and cross section data. *Econometrica*, *46*, 69–85.

Nelson, R. R., & Winter, S. G. (1982). *An evolutionary theory of economic change*. Cambridge, MA: Harvard University Press.

OECD. (2009). *Top barriers and drivers to SME internationalisation*. Report by working party on SMEs and entrepreneurship. OECD.

Ortega-Argils, R., Vivarelli, M., & Voigt, P. (2009). R&D in SMEs: A paradox? *Small Business Economics*, *33*, 3–11.

Petrin, A., & Levinsohn, J. (2012). Measuring aggregate productivity growth using plant-level data. *The RAND Journal of Economics*, *43*, 705–725.

Plehn-Dujowich, J. M. (2009). Entry and exit by new versus existing firms. *International Journal of Industrial Organization*, *27*, 214–222.

Silverberg, G., Dosi, G., & Orsenigo, L. (1988). Innovation, diversity and diffusion: A self-organisation model. *Economic Journal*, *98*, 1032–1054.

Silverberg, G., & Verspagen, B. (1995). An evolutionary model of long term cyclical variations of catching up and falling behind. *Journal of Evolutionary Economics*, *5*, 209–27.

Sutton, J. (1998). *Technology and market structure: Theory and evidence*. Cambridge, MA: MIT Press.

Syverson, C. (2011). What determines productivity? *Journal of Economic Literature*, *49*, 326–65.

Van Beveren, I. (2012). Total factor productivity estimation: A practical review. *Journal of Economic Surveys*, *26*, 98–128.

Winter, S. G. (1987). Knowledge and competence as strategic assets. In D. J. Teece (Ed.), *The competitive challenge: Strategies for industrial innovation and renewal*. Cambridge, MA: Ballinger.

Wooldridge, J. (2009). *Correlated random effects models with unbalanced panels*. Manuscript (version July 2009). Michigan State University.