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

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WORKING PAPER SERIES

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

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

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Abstract

This paper presents a broad set of empirical regularities about selection and market shares reallocation 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*-firms reallocation of shares. The evidence corroborates that within-firm learning prevails over competitive selection. Second, we address the “strength” of reallocation by exploring if and to what extent firm growth rates are shaped by relative productivity levels in deviation from industry average and by the over time variation of productivities themselves. The econometric analysis accounts for both the dynamic dimension of the selection process and idiosyncratic firm-specific factors. We find that changes, rather than relative levels, are the dominant productivity-related determinant of relative growth rates.

JEL codes: C23, D22, L10, L20, O47

Keywords: firms heterogeneity, sectoral productivity decomposition, corporate growth, productivity, market selection, firm-industry dynamics

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1 Introduction

Several empirical studies have documented by now the turbulent dynamics underlying the process of productivity growth in manufacturing sectors.¹ In interpreting such evidence, a central concern has been the relative importance for aggregate performances (say, productivity growth) of, first, the reallocation of shares from less productive to more productive firms - the so called “between effect”; second, firm-specific productivity dynamics - the so called “within effect”; and, third, the turnover between entrant and exiters.

Most studies (Baily et al., 1992; Griliches and Regev, 1995; Baldwin and Gu, 2006; Foster et al., 2001) do find significant rates of input and output reallocation across firms even within 4-Digit industries. The process is shaped by a good deal of turnover with high flows of entry and exit, with about half of the new firms dying within the first 5 years (Bartelsman et al., 2005). As for the contribution of this “churning” to the overall productivity growth, the evidence is more mixed, with some works finding small effects (Baily et al., 1992; Griliches and Regev, 1995, respectively for USA and Israel) and others more important gains (Baldwin and Gu, 2006, for Canada).

The evidence supporting selection among incumbents is similarly weak. If we interpret the between component as a measure of competitive-driven selection dynamics, then what most studies show is that idiosyncratic learning (the within term) usually generates a larger contribution to productivity growth than shares reallocation among firms. In fact, some evidence as Disney et al. (2003) for UK shows even negative between effect.

An important caveat is that these studies adopt different decomposition formulas, and different units of analysis (firms or plants), so that a comparison is not straightforward.² A first contribution of the present study is therefore to provide a unitary framework for a comparison across countries. We study decompositions of productivity growth on firm-level data on the USA and major European economies, namely France, Germany and the UK, in turn characterised by different institutional setups, plausibly influencing also the competition process.

A further limitation is that the “between” part of the decomposition of productivity growth gives only a first, indirect measure of the selection amongst incumbent. Indeed, it just reveals which fraction of productivity growth is accounted for by the reallocation of shares to the most productive firms. A more compelling question concerns the extent to which the relative productivities of firms influence their growth process. The empirical literature has not given the deserved attention to the analysis of this relationship, even if it is at the center of many models of industry dynamics, both of neoclassical and

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

²So, for example, Baldwin and Gu (2006) find, too, a negative between term in most sectors, when using the Griliches and Regev (1995) decomposition formula. See Foster et al. (2001) for a discussion of sensitivity of decomposition results to different methodologies. See Petrin and Levinsohn (2012) for specific treatment of decompositions based on plant-level data.

evolutionary roots, which predict a relationship between the relative growth of a firm and its relative efficiency. The neoclassical perspective includes the models by Jovanovic (1982), Hopenhayn (1992), Ericson and Pakes (1995) and the more recent Luttmer (2007). On the evolutionary side, formalizations include the classical Nelson and Winter (1982) and also a class of models (see especially Silverberg et al., 1988; Dosi et al., 1995) which interpret the selection amongst firms via some mechanism of replicator dynamics type.

Most of these theories predict that comparatively more productive firms should gain market and grow more. This can happen because the more efficient a firm is, in terms of relative productivity, the lower the price it charges, thus capturing an higher share of the demand. Alternatively, selection occurs because the differential efficiency of firms spur their differential growth via profitability, as only the most productive firms - making more profits - can invest and grow, especially in presence of imperfect capital markets.

Bottazzi et al. (2010) is one of the first attempts to address empirically the relationship between relative efficiency and growth rates through firm level regressions. The main finding, based on the analysis of French and Italian manufacturing firms, is that the variance of growth rates is explained only to a little extent by the variance of relative productivities or profitabilities. The drawback of such econometric analysis, however, is that, by using a standard Fixed Effects estimator, the contribution of a firm's average efficiency over time is washed away.

This paper builds on Bottazzi et al. (2010), extending to other countries, and also applying different panel techniques to disentangle, within firm unobserved fixed effect, the part which correlates with productivity from the independent part. The regression results allow to assess the relative importance of differences in productivity levels vs. productivity changes over time as determinants of firm growth.

The paper is organized as follows. In Section 2 we describe the dataset of European and USA firms. In Section 3 we present the results of the decomposition of productivity growth. In Section we 4 turn to panel data regressions. Section 5 concludes.

2 Data and Variables

The present analysis draws upon two distinct firm-level datasets. For USA firms, our source is the North-American section of COMPUSTAT. The time period covered goes from 2000 to 2007. For the European countries (France, Germany, and the UK) we use Amadeus, a commercial database provided by Bureau van Dijk. The edition at our disposal (March 2010) contains balance sheet and income statement information about over 14 Million European firms. The data are standardized to allow comparisons across countries. The database includes up to ten years of accounting information of firms that have to file their accounts by law. Because of different disclosure requirements, coverage varies across countries. Moreover, the yearly update drops all the firms for which there is

no information in the last five years, so that coverage also varies by year. In order to have a time interval with a good coverage of the variables of interest, the empirical analysis spans the period 2000-2007 for France and United Kingdom, while the sample period is 2001-2007 for Germany.³

We concentrate the analysis on manufacturing industries. Covered sectors correspond to the 2-digits international ISIC Rev.4 classification. We are interested in corporate performances across countries as revealed by two major dimensions: productivity and growth. As a measure of productivity, we use the simple ratio of value added, at constant prices, over the number of employees.⁴ Firm growth is measured as the log difference of sales, in two consecutive years. All the nominal variables are deflated with appropriate sectoral production price indexes, from EUROSTAT and from the BLS (base year 2005).

3 Decomposition of productivity growth

Industry-level productivity growth is the aggregate outcome of firms' micro-dynamics. Some firms grow and improve their performances, some others shrink and even disappear, and new firms come into the market game. Incumbent firms, in particular, contribute to aggregate growth by means of two distinct processes. On one hand, they may learn, innovate, imitate and thus improve the efficiency of their productive operations. This is referred to as the *within* component of productivity growth. On the other hand, incumbent firms may gain or lose market shares in favour of more or less efficient firms, contributing to the so-called *between* component of aggregate productivity growth. The relative magnitude of the two components represents a first evidence on the importance of market selection mechanisms. A bigger within component tells that the dynamics of productivity growth is shaped, above all, by improvements which take place inside the firm itself. A bigger between component, on the other hand, is a sign that competition forces lead aggregate outcomes.

In order to disentangle these two forces, we first define a general index of the aggregate productivity of sector j as a weighted sum of individual firms' productivities

$$\tilde{\Pi}_{j,t} = \sum_{i \in j} s_{i,t} \Pi_{i,t} \quad , \quad (1)$$

where $\Pi_{i,t}$ is the labour productivity of firm i at time t , and $s_{i,t}$ is the share of firm i in

³We also leave out firms with less than 20 employees, for comparison with Bottazzi et al. (2010) performing similar analysis on France and Italy.

⁴As standard, we define value added as revenues minus operating costs (cost of labour excluded). Figures are directly available in Amadeus, while only sales and total costs (cost of labour included) are available in Compustat. Cost of labour needs therefore to be constructed, and added back to the difference between sales and total costs in order to get an homogeneous proxy of value added. Following Brynjolfsson and Hitt (2003), we compute the cost of employees by multiplying the number of employees for the average sectoral cost of labour as reported by the BLS at the 4-digits level of disaggregation.

sector j . Then, we can decompose the index according to the following formula

$$\Delta \tilde{\Pi}_{j,t} = \Delta \sum_{i \in j} s_{i,t} \Pi_{i,t} = \sum_{i \in j} \bar{s}_i \Delta \Pi_{i,t} + \sum_{i \in j} \Delta s_{i,t} \bar{\Pi}_i \quad , \quad (2)$$

where Δ is the difference between end and base year, and a bar over a variable indicates the average of the variable over the two years. The two terms on the right hand side of the second equality identify the two components. The first term is the *within-firm* effect, i.e the change in productivity of firms weighted by their average shares. The second term is the *between-firms* effect, i.e. the variation in firms' shares weighted by average productivity levels.⁵ Using this formula, we compute the contribution of the two components for each pair of consecutive years in our sample, and then sum them over time. Formally, the decomposition is

$$\sum_t \Delta \tilde{\Pi}_{j,t} = \sum_t \sum_{i \in j} \bar{s}_i \Delta \Pi_{i,t} + \sum_t \sum_{i \in j} \Delta s_{i,t} \bar{\Pi}_i \quad , \quad (3)$$

where the within and between components are the two terms of the sum.⁶

Two comments are in order about Equation (3). First, since by construction the sum of shares of incumbent firms (without entry and exit) 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. Second, one can imagine different ways to measure the share of a firm in the industry. Here we consider employment shares, as this choice ensures that we are decomposing a standard, aggregate labour productivity index. However, this needs not to be the most appropriate way to account for the process of selection: firms do primarily compete in the goods market, and their expansion or contraction is revealed in terms of product shares, not employment shares. We will come back to the dynamics of firm growth as measured by sales in the panel regressions of the next Section.

Table 1 presents the results obtained from the decomposition as of Equation (3), according to sectors and countries. Figure 1 offers a summary picture of the exercise via violin plots: for each country, white violins report the sectoral distribution of the shares of the between effect, while shaded violins refer to the corresponding contribution of the within term.

The most striking finding is the predominance of the within component in the great majority of sectors. The median value of the between component across sectors is indeed

⁵This decomposition, as in Griliches and Regev (1995), does not separate out the covariance effect. Notice, however, that this simplification is not going to affect in any way the analysis we are interested into. Indeed, it can be shown that the covariance term picks out half of the within effect and half of the between effect, leaving their relative magnitude unchanged.

⁶Notice that the percentage contribution of each component obtained with this formula is equivalent to the weighted sum of the yearly contributions. Take for example the within-firm effect. Its total contribution will be equal to $(\sum_t \sum_{i \in j} \bar{s}_i \Delta \Pi_{i,t}) / (\sum_t \Delta \tilde{\Pi}_{j,t}) = \sum_t [(\frac{\sum_{i \in j} \bar{s}_i \Delta \Pi_{i,t}}{\Delta \tilde{\Pi}_{j,t}}) (\frac{\Delta \tilde{\Pi}_{j,t}}{\sum_t \Delta \tilde{\Pi}_{j,t}})]$.

Table 1: Decomposition of labor productivity growth

| | FRANCE | | GERMANY | | UK | | USA | |
|-------------------------|---------------|----------------|---------------|----------------|---------------|----------------|---------------|----------------|
| | <i>Within</i> | <i>Between</i> | <i>Within</i> | <i>Between</i> | <i>Within</i> | <i>Between</i> | <i>Within</i> | <i>Between</i> |
| 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 |

Decomposition based on Equation (3), over the period from 2000 (2001 for Germany) to 2007. Values are normalized as shares of total productivity growth.

quite low everywhere: it is 6% in UK, 8% in the USA, 10% in France, and strikingly -2% in Germany. This result witnesses against any simplistic view of the power of selection mechanism. 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.

Further, despite some degree of variability in the estimates, the main pattern of a weak or lacking power of selection holds irrespective of the country analyzed. Indeed, the violins of the two components are considerably overlapping in their central part, and the median values of the sectoral distribution of the two components (the central line in each violin) are quite similar across countries: close to zero for the between component, and near one for the within component. This suggests that weak competitive selection indeed does not vary much across different institutional and other country-specific features. Somewhat contrary to the common wisdom, competitive forces do not seem to be more effective in more “market-oriented” economies, such as the UK and the USA, as compared to continental Europe.

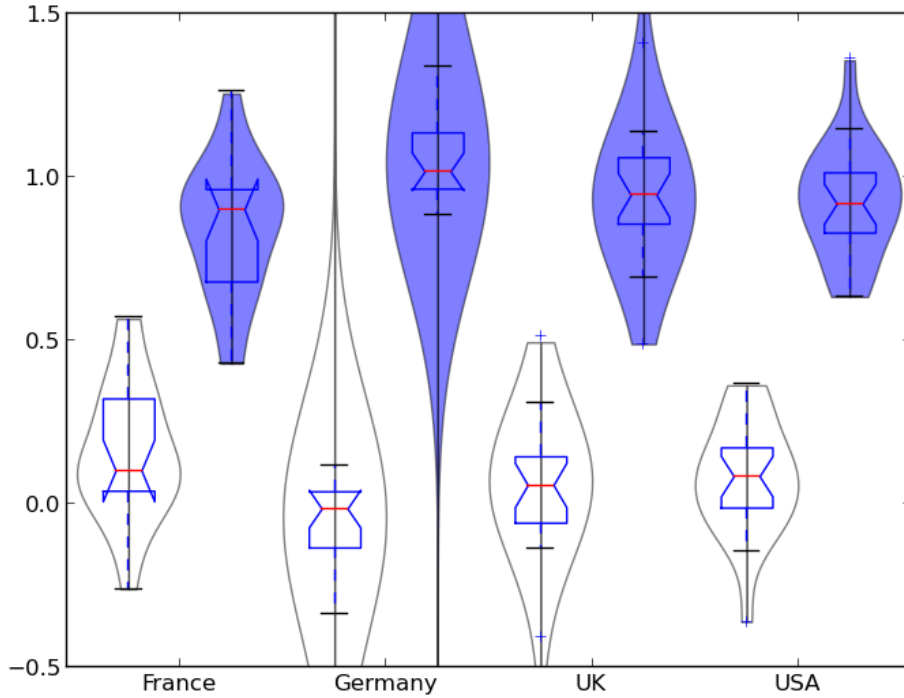


Figure 1: Distributions of sectoral *between* and *within* components across countries. Each violin reports a box plot and a kernel density to each side of the box plot. For each country, the white violin and the shaded violin refer, respectively, to the between and within component. Distributions, median values and interquartile ranges are computed according to Table 1.

4 Regression analysis

The decomposition exercise allows to assess the relative importance of firm-specific learning vs. selection/reallocation across firms as the drivers of aggregate productivity growth. In this section, we focus on the selection/reallocation mechanism by analyzing the direct effect of productivity on firm growth within a regression framework. We seek to disentangle two features of the mechanism. The first question pertains to the strength of reallocation, which we address by measuring if and to what extent firm growth is accounted for by relative productivity. Second, we mean to unravel the dynamic features of the productivity-growth relationship. The former exercise focuses upon the *levels* of productivity relative to other firms in the same industry as the key potential driver of firm changing market shares and growing. In the latter exercise, instead, we consider the impact of over time changes of relative productivity - its relative growth rates - upon corporate growth.

We here compute firm growth in terms of growth of sales, a measure which directly links to the competitive success (or failure) on the product market. The analysis exploits

Table 2: 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 ^a (0.009) | -0.200 ^a (0.008) | 0.271 ^a (0.037) | -0.347 ^a (0.042) | 0.180 ^a (0.014) | -0.168 ^a (0.014) | 0.185 ^a (0.042) | -0.124 ^a (0.041) |
| Beverages | 0.207 ^a (0.019) | -0.137 ^a (0.019) | 0.167 ^b (0.074) | -0.434 ^a (0.058) | 0.250 ^a (0.028) | -0.109 ^a (0.030) | 0.292 ^a (0.059) | -0.266 ^a (0.080) |
| Textile | 0.285 ^a (0.013) | -0.283 ^a (0.014) | 0.265 ^a (0.099) | -0.247 ^a (0.091) | 0.168 ^a (0.014) | -0.124 ^a (0.015) | 0.288 ^b (0.139) | -0.209 (0.148) |
| Wearing | 0.246 ^a (0.016) | -0.193 ^a (0.016) | 0.039 (0.070) | -0.195 ^a (0.065) | 0.212 ^a (0.022) | -0.144 ^a (0.024) | 0.147 ^a (0.034) | -0.113 ^a (0.034) |
| Leather | 0.387 ^a (0.026) | -0.375 ^a (0.026) | 0.379 ^a (0.047) | -0.332 ^a (0.055) | 0.197 ^a (0.040) | -0.106 ^b (0.046) | 0.453 ^a (0.058) | -0.350 ^a (0.062) |
| Wood | 0.280 ^a (0.013) | -0.254 ^a (0.013) | 0.545 ^a (0.102) | -0.432 ^a (0.084) | 0.165 ^a (0.021) | -0.197 ^a (0.022) | 0.192 ^a (0.031) | -0.210 ^a (0.057) |
| Paper | 0.107 ^a (0.013) | -0.119 ^a (0.014) | 0.418 ^a (0.046) | -0.254 ^a (0.044) | 0.116 ^a (0.015) | -0.084 ^a (0.016) | 0.285 ^a (0.063) | -0.272 ^a (0.061) |
| Printing | 0.245 ^a (0.014) | -0.193 ^a (0.014) | 0.210 ^b (0.090) | -0.061 (0.078) | 0.226 ^a (0.015) | -0.215 ^a (0.016) | -0.093 (0.094) | -0.317 ^a (0.082) |
| Coke & petroleum | 0.000 (0.043) | 0.030 (0.039) | 0.464 ^a (0.124) | -0.556 ^a (0.096) | 0.102 ^b (0.052) | -0.127 ^b (0.050) | -0.076 (0.058) | -0.068 (0.061) |
| Chemical | 0.150 ^a (0.011) | -0.157 ^a (0.012) | 0.195 ^a (0.029) | -0.174 ^a (0.029) | 0.112 ^a (0.010) | -0.082 ^a (0.011) | 0.155 ^a (0.024) | -0.207 ^a (0.026) |
| Pharmaceutical | 0.345 ^a (0.028) | -0.302 ^a (0.024) | 0.259 ^a (0.033) | -0.151 ^a (0.035) | 0.193 ^a (0.023) | -0.125 ^a (0.020) | 0.252 ^a (0.026) | -0.247 ^a (0.023) |
| Rubber and plastic | 0.198 ^a (0.012) | -0.221 ^a (0.011) | 0.133 ^a (0.041) | -0.161 ^a (0.042) | 0.179 ^a (0.015) | -0.164 ^a (0.015) | 0.165 ^a (0.049) | -0.141 ^a (0.044) |
| Other non-metallic | 0.256 ^a (0.014) | -0.262 ^a (0.013) | 0.446 ^a (0.055) | -0.369 ^a (0.046) | 0.202 ^a (0.018) | -0.228 ^a (0.017) | 0.136 ^b (0.057) | -0.260 ^a (0.067) |
| Basic metals | 0.242 ^a (0.016) | -0.257 ^a (0.016) | 0.232 ^a (0.034) | -0.167 ^a (0.033) | 0.261 ^a (0.022) | -0.255 ^a (0.023) | 0.139 ^a (0.044) | -0.160 ^a (0.044) |
| Fabricated metal | 0.380 ^a (0.008) | -0.342 ^a (0.008) | 0.200 ^a (0.033) | -0.273 ^a (0.030) | 0.234 ^a (0.011) | -0.213 ^a (0.012) | 0.381 ^a (0.038) | -0.229 ^a (0.039) |
| Machinery | 0.350 ^a (0.012) | -0.294 ^a (0.011) | 0.297 ^a (0.027) | -0.199 ^a (0.025) | 0.189 ^a (0.012) | -0.152 ^a (0.013) | 0.216 ^a (0.017) | -0.222 ^a (0.019) |
| Computer & electronic | 0.249 ^a (0.017) | -0.239 ^a (0.015) | 0.167 ^a (0.037) | -0.239 ^a (0.044) | 0.200 ^a (0.010) | -0.179 ^a (0.010) | 0.249 ^a (0.010) | -0.154 ^a (0.009) |
| Electrical | 0.302 ^a (0.018) | -0.400 ^a (0.018) | 0.271 ^a (0.037) | -0.188 ^a (0.033) | 0.210 ^a (0.014) | -0.204 ^a (0.015) | 0.323 ^a (0.047) | -0.151 ^a (0.041) |
| Motor Vehicles | 0.242 ^a (0.020) | -0.273 ^a (0.020) | 0.133 ^a (0.051) | -0.240 ^a (0.042) | 0.136 ^a (0.024) | -0.220 ^a (0.021) | 0.304 ^a (0.072) | -0.203 ^a (0.076) |
| Other transport | 0.240 ^a (0.030) | -0.282 ^a (0.029) | 0.336 ^b (0.143) | -0.222 (0.156) | 0.154 ^a (0.020) | -0.107 ^a (0.020) | 0.286 ^a (0.065) | -0.288 ^a (0.062) |
| Furniture | 0.219 ^a (0.019) | -0.200 ^a (0.020) | 0.635 ^a (0.092) | -0.630 ^a (0.120) | 0.222 ^a (0.023) | -0.123 ^a (0.025) | 0.315 ^a (0.060) | -0.085 (0.064) |
| Other manufacturing | 0.377 ^a (0.020) | -0.318 ^a (0.023) | 0.210 ^a (0.057) | -0.269 ^a (0.043) | 0.200 ^a (0.012) | -0.205 ^a (0.012) | 0.177 ^a (0.025) | -0.137 ^a (0.020) |

Note. Fixed effects estimates of Equation (5), standard error in parenthesis. ^a $p < 0.01$, ^b $p < 0.05$, ^c $p < 0.10$.

the panel structure of the data, allowing to focus on the productivity-growth nexus while controlling for time-invariant unobserved characteristics of the firms.

4.1 The effect of productivity on growth

Within each industry, we model the growth-productivity relationship through the following linear model with additive heterogeneity

$$g_{i,t} = a + b_t + \sum_{l=0}^L \beta_l \pi_{i,t-l} + u_i + \epsilon_{i,t} \quad (4)$$

where $g_{i,t}$ denotes the growth rate of firm i in terms of log-differences of sales between two consecutive years, $\pi_{i,t}$ is the (log) labour productivity, b_t is a time dummy, $l = \{0, \dots, L\}$ with L the longest lag length considered, u_i is a firm-specific time invariant unobserved effect, and $\epsilon_{i,t}$ the usual error term. The presence of time dummies is equivalent to consider the variables in deviation from their cross-sectional (industry) average, so that what matters is only the relative efficiency of firms in the same industry.

This specification allows for a distributed lag in the effects of the independent variable, picking up possible adjustment times between changes in relative productivities and changes in the growth rates. Lagged values are also required for the strict exogeneity of the error term imposed for consistency of standard panel estimators.⁷

Based on sequential rejection of the statistical significance of longer lags structure, we choose as our baseline equation a model with $L = 1$:

$$g_{i,t} = a + b_t + \beta_0 \pi_{i,t} + \beta_1 \pi_{i,t-1} + u_i + \epsilon_{i,t} \quad (5)$$

Estimates of Equation (5) via the Fixed Effects estimator are shown in Table 2. In almost the totality of sectors across the four countries, the coefficients β_0 and β_1 are significant at the 1% level. This suggests that relative productivity levels, both at time t and at time $t - 1$, have an effect on firm growth rates. The effect is robust both to sector and to country specificity.

Concerning the sign and the magnitude, strong regularities emerges across sectors and countries, as we show graphically in Figure 2. For each country, we display two shaded violin plots, representing the distribution of the sectoral coefficients β_0 (the leftmost violin) and β_1 (the rightmost violin), and a white violin in the middle, which represents the sum of the two coefficients. We observe that the two coefficients are quite stable in absolute value, with a median across sectors of about 0.2 in all the countries. Moreover, values of β_0 and β_1 are on average equal in magnitude and opposite in sign, as it is apparent from the white violins, all tightly spread around a median value of about zero.

These results suggest two main conclusions. Firstly, the effect of the levels of productivity is ambiguous: positive at time t and negative at time $t - 1$. Secondly, this ambiguity would disappear if one looked at the first difference of the levels, $\pi_{i,t} - \pi_{i,t-1}$, that is at the effect of productivity growth, which is positive on average. We will come back to this point in Section 4.3 below.

⁷The presence of significant lag values ensures that there are no shocks to the dependent variable that are correlated with past values of the independent variable. More formally, strict exogeneity ($E(\epsilon_{i,t} | \pi_{i,s}, u_i) = 0, \forall t, s$) 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.

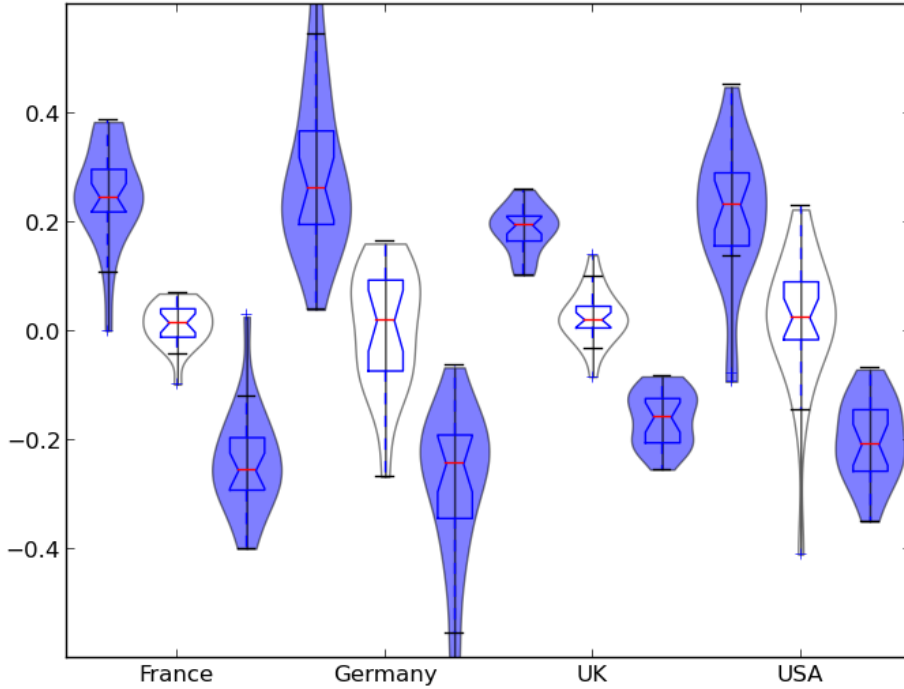


Figure 2: Distributions of sectoral β_0 , β_1 and $\beta_0 + \beta_1$ across countries. For each country, the leftmost and the rightmost shaded violin refer, respectively, to β_0 and β_1 . The middle white violin refers to the sum of the two coefficients. Distributions, median values and interquartile ranges are computed according to Table 2.

4.2 The explanatory power of productivity

The estimates of β_0 and β_1 from Equation (5) stand for elasticities: a 1% increase in productivity at time t or $t - 1$ is related to an average change in sales growth of about 0.2. However, despite statistical significance, the coefficient estimates do not pinpoint the “strength” of the economic relevance in the association between the two variables, and thus they do not say much about the extent to which firms are selected according to their relative productivity. To assess the strength of competitive selection, one needs to resort to a coefficient of determination, measuring the variance of $g_{i,t}$ explained by current and past relative productivity. This is done in Bottazzi et al. (2010), just with respect to $\pi_{i,t}$. Their estimates on France and Italy suggest that relative productivity appear to “explain” roughly between 3% and 5% of the overall variance in growth rates, while the contribution of unobserved heterogeneity (the firm fixed effects) is much larger.

However, a model with firm fixed effects and just current productivity as regressors does not necessarily satisfy exogeneity conditions. Instead, the dynamic specification of Equation (5) ensures that exogeneity conditions are met so that the standard within-group estimator applied here above gives unbiased coefficients. A further issue with Fixed

Effects estimates of Equation (5) is that they systematically neglect the “productivity-related effect” hidden within the whole firm-specific effect u_i . To see why, 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 effect, while this average effect is clearly a part of the explanatory power of productivity.

What one needs to do is to disentangle, within the unobserved effect u_i , the part which is correlated with productivity from the part which is not. We therefore re-estimate Equation (5) by Correlated Random Effects. This entails a standard Random Effects estimation of the following model

$$g_{i,t} = a + b_t + \beta_0\pi_{i,t} + \beta_1\pi_{i,t-1} + \beta_{0a}\bar{\pi}_i + \beta_{1a}\bar{\pi}_{i,-1} + c_i + \epsilon_{i,t} \quad , \quad (6)$$

where $\bar{\pi}_i$ and $\bar{\pi}_{i,-1}$ are the time series averages of the (log) productivity up to time t and time $t - 1$, respectively, while c_i is the new unobserved firm-specific heterogeneity term, uncorrelated with the productivity regressors after controlling for their averages. The advantage with respect to Equation (5) is that we are explicitly taking into account the contribution to sales growth also of productivity averages through time.⁸

Thus, we can compute the following measure of total explained variance

$$S^2 = \frac{Var(\beta_0\pi_{i,t} + \beta_1\pi_{i,t-1} + \beta_{0a}\bar{\pi}_i + \beta_{1a}\bar{\pi}_{i,-1})}{Var(g_{i,t})} \quad . \quad (7)$$

The traditional coefficient of determination

$$R^2 = \frac{Var(\beta_0\pi_{i,t} + \beta_1\pi_{i,t-1} + \beta_{0a}\bar{\pi}_i + \beta_{1a}\bar{\pi}_{i,-1}) + Var(c_i)}{Var(g_{i,t})} \quad (8)$$

takes into account 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.⁹

Table 3 reports the values of S^2 and R^2 across countries and industries. Values of R^2 show that our simple linear model with levels and averages of productivity plus firm-level heterogeneity is able to account for around 40% and 65% of the variance in sales growth rates. Median values across sectors are 0.41 for France, 0.66 for Germany, 0.39 for the UK and 0.51 for the USA. The values of S^2 , capturing only the contribution of the

⁸Note that Random Effects estimation of Equation (6) does not change the value of the coefficients β_0 and β_1 . Indeed, as shown in Mundlak (1978) for balanced panels and Wooldridge (2009) for unbalanced panels, the coefficients obtained from a Fixed Effects estimation are equal to the corresponding coefficients from a Random Effects estimation of the same equation augmented with the time averages of the regressors.

⁹More precisely, R^2 also includes the contribution of time dummies. These are found to account only for a negligible part of total variation in our case, and we thus omit them from the computation.

Table 3: 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 |

Note. S^2 and R^2 from random effects estimation of Equation (6).

productivity regressors (both levels and averages), are in median 0.19 for France, 0.18 for Germany, 0.14 and 0.15 for USA. That is, productivity variables account for between one fifth and one sixth of the variance in firms' growth rates. This is a modest contribution, although considerably higher than what found in Bottazzi et al. (2010). Correspondingly, firm fixed idiosyncratic effects have a smaller contribution as compared to Bottazzi et al. (2010), although they still represents a fundamental determinant of firm growth.

Overall, there seems to be some explanatory power of productivity variables, leaving some more room for an effective working of competitive selection as compared to the weak or lacking competitive selection suggested by the small between component in the decomposition exercise. Recall however that the S^2 actually results from two opposing effects, a positive one from contemporaneous productivity and negative one from the lagged variable. The next section tackles these seemingly puzzling findings.

4.3 Productivity levels and productivity changes

The evidence from regression analysis so far tells about two patterns, common across sectors and countries. First, a clear result on the lag structure of the productivity-growth

relationship, in which the effect of productivity at time t is, on average, equal and opposite in sign to the effect at time $t-1$. Second, the robust finding that a model with lags explains at least part of firm growth variance. Coupling the two findings, one can conjecture that the actual drivers of firm growth do not rest in the relative *level* of productivity at any time period, but rather in their *variation* through time.

To test the importance of relative productivity levels vis-à-vis productivity changes, we separate the S^2 computed for the productivity variables from Equation (6) into a static component, related to levels, and a dynamic component, capturing variation over time. Rewrite Equation (5) as

$$g_{i,t} = a + b_t + \beta_{\Delta}\Delta\pi_{i,t} + \beta_m\bar{\pi}_{i,t} + u_i + \epsilon_{i,t} \quad (9)$$

where $\Delta\pi_{i,t}$ is the growth rate of productivity (in log differences over two consecutive years), which accounts for the *dynamics* of differential efficiency, while $\bar{\pi}_{i,t}$ is the average productivity level over t and $t-1$, which captures the absolute differential efficiency among firms.¹⁰ Under the hypothesis that firms are selected and grow mostly according to their “static” relative efficiency, we 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.

We first estimate via Random Effects the equation

$$y_{i,t} = a + b_t + \beta_{\Delta}\Delta\pi_{i,t} + \beta_m\bar{\pi}_{i,t} + \beta_{\Delta a}\bar{\Delta}\pi_i + \beta_{ma}\bar{\bar{\pi}}_{i,t} + c_i + \epsilon_{i,t} \quad , \quad (10)$$

and then 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 (7).¹¹

Results are reported in Table 4, while a graphical representation is presented in Figure 3. In basically all sectors, and irrespective of the country considered, 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 always nearly identical to the overall S^2 reported in Table 3. We thus confirm the above conjecture that the driver of the explanatory power of productivity variables entirely stems from efficiency changes more than from absolute differences of productivity levels across firms. Notice that such 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, significant, although relatively small effects of reallocation and market selection among firms can only

¹⁰Notice that β_{Δ} and β_m are related to the coefficients of Equation (5) through $\beta_0 = \frac{\beta_m}{2} + \beta_{\Delta}$ and $\beta_1 = \frac{\beta_m}{2} - \beta_{\Delta}$.

¹¹When separating out the effect of $\Delta\pi_{i,t}$ from that of $\bar{\pi}_{i,t}$ we assign the covariance term in equal parts to each of the two components.

Table 4: Productivity-growth relationship, 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 & 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 & 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 |

Note. $S^2_{\Delta\pi_{i,t}}$ and $S^2_{\bar{\pi}_{i,t}}$ from random effects estimation of Equation (10).

be detected in terms of relative dynamics in efficiencies, while standard decompositions only consider static efficiency differentials.

5 Conclusions

This paper contributes to the analysis of the workings of market selection and reallocation in four different countries, characterised 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 firm. 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 of market selection and reallocation of market shares to the dynamics of aggregate industry productivity.

We next search more directly for the fingerprints of competitive selection, by estimating the relationship between relative efficiency levels and relative growth rates at the firm level. From the findings, the power of selection the mechanisms, although still modest,

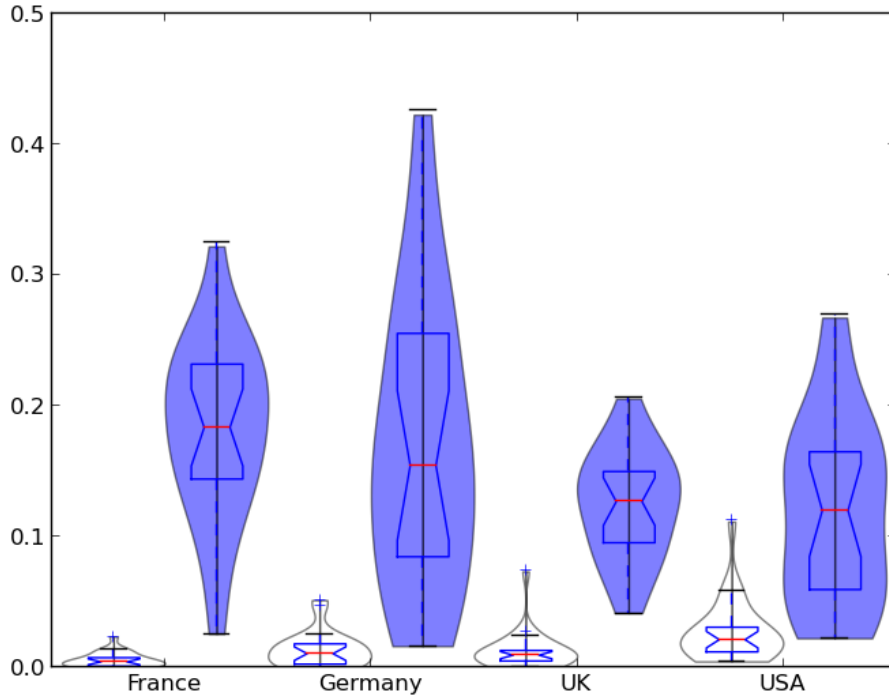


Figure 3: Distributions of sectoral $S^2_{\Delta\pi_{i,t}}$ and $S^2_{\bar{\pi}_{i,t}}$ across countries. For each country, the white violin and the shaded violin refer, respectively, to $S^2_{\Delta\pi_{i,t}}$ and $S^2_{\bar{\pi}_{i,t}}$. Distributions, median values and interquartile ranges are computed according to Table 4.

appears stronger as compared to the decomposition exercise and to the results of previous relevant studies. The explanatory power associated to 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 differences over time, that is on the rates of productivity growth, while the distance in relative efficiency among firms does not contribute at all.

All this evidence does but reinforce the view that a relatively naive form of replicator-type competitive process primarily based on productive efficiency - as roughly proxied by real value added per employee - does not seem to be very effectively at work. The analysis suggests that indeed a significant role is played by *relative changes* in productivities, rather than *relative absolute levels*, as most evolutionary models of selection would predict, from Nelson and Winter (1982) to Dosi et al. (1995) all the way to equilibrium models *à la* Jovanovic (1982).

How do we interpret all this? 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) (see also Dosi et al., 2013), which are also the *loci* of competition. So, for

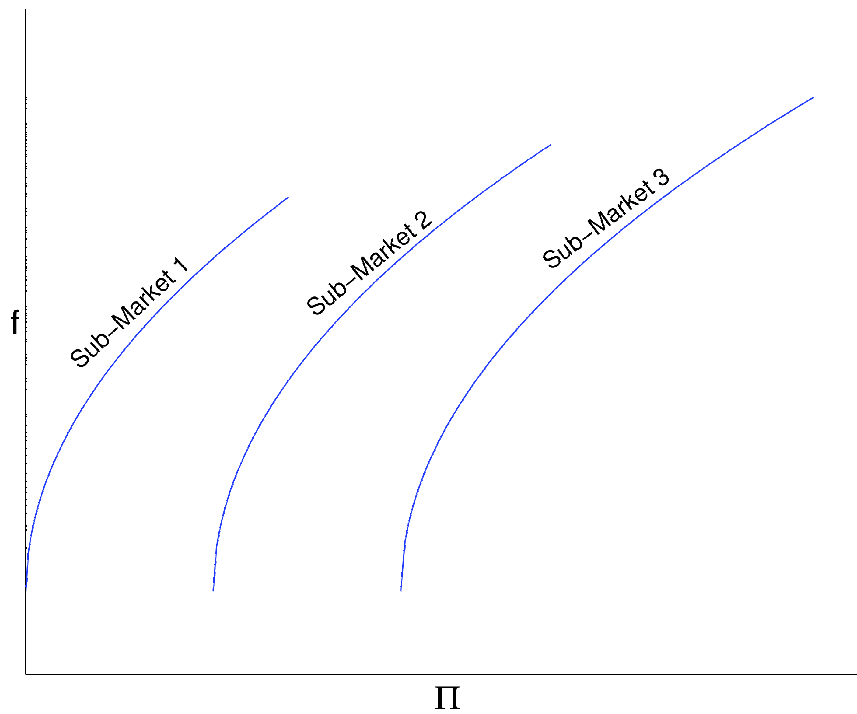


Figure 4: Submarkets landscape.

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) and some measure of fitness (f) of the organization, like in Figure 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 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 leads, other things being equal, an improvement in fitness. And this is precisely what relative rates of productivity growth capture.

Of course, the foregoing interpretation 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 “satisficing” aspirations of the various firms, their internal structure and in particular financial conditions, etc. But also this interpretation entails testable propositions on the relationship between revealed

behavioural patterns and corporate growth.

References

- BAILY, M. N., C. HULTEN, AND D. CAMPBELL (1992): “Productivity Dynamics in Manufacturing Plants,” *Brookings Papers on Economic Activity. Microeconomics*, 4, 187–267.
- BALDWIN, J. R. AND W. GU (2006): “Plant turnover and productivity growth in Canadian manufacturing,” *Industrial and Corporate Change*, 15, 417–465.
- BARTELSMAN, E., S. SCARPETTA, AND F. SCHIVARDI (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. AND M. DOMS (2000): “Understanding Productivity: Lessons from Longitudinal Microdata,” *Journal of Economic Literature*, 38, 569–594.
- BOTTAZZI, G., G. DOSI, N. JACOBY, A. SECCHI, AND F. TAMAGNI (2010): “Corporate performances and market selection: some comparative evidence,” *Industrial and Corporate Change*, 19, 1953–1996.
- BRYNJOLFSSON, E. AND L. M. HITT (2003): “Computing Productivity: Firm-Level Evidence,” *Review of Economics and Statistics*, 85, 793–808.
- DISNEY, R., J. HASKEL, AND Y. HEDEN (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 *Perspectives on Innovation*, ed. by F. Malerba and S. Brusoni, Cambridge University Press.
- DOSI, G., A. GAMBARDELLA, M. GRAZZI, AND L. ORSENIGO (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 *The Third Industrial Revolution in Global Perspective*, ed. by G. Dosi and L. Galambos, Cambridge University Press.
- DOSI, G., O. MARSILI, L. ORSENIGO, AND R. SALVATORE (1995): “Learning, Market Selection and Evolution of Industrial Structures,” *Small Business Economics*, 7, 411–36.
- ERICSON, R. AND A. PAKES (1995): “Markov-Perfect Industry Dynamics: A Framework for Empirical Work,” *Review of Economic Studies*, 62, 53–82.

- FOSTER, L., J. HALTIWANGER, AND C. J. KRIZAN (2001): *New Developments in Productivity Analysis*, University of Chicago Press, chap. Aggregate Productivity Growth: Lessons from Microeconomic Evidence, 303–372.
- GRILICHES, Z. AND H. REGEV (1995): “Firm productivity in Israeli industry 1979-1988,” *Journal of Econometrics*, 65, 175–203.
- 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.
- MUNDLAK, Y. (1978): “On the Pooling of Time Series and Cross Section Data,” *Econometrica*, 46, 69–85.
- NELSON, R. R. AND S. G. WINTER (1982): *An Evolutionary Theory of Economic Change*, Harvard University Press.
- PETRIN, A. AND J. LEVINSOHN (2012): “Measuring aggregate productivity growth using plant-level data,” *The RAND Journal of Economics*, 43, 705–725.
- SILVERBERG, G., G. DOSI, AND L. ORSENIGO (1988): “Innovation, Diversity and Diffusion: A Self-organisation Model,” *Economic Journal*, 98, 1032–1054.
- SUTTON, J. (1998): *Technology and Market Structure: Theory and Evidence*, MIT Press.
- SYVERSON, C. (2011): “What Determines Productivity?” *Journal of Economic Literature*, 49, 326–65.
- WOOLDRIDGE, J. (2009): “Correlated random effects models with unbalanced panels,” Manuscript (version july 2009), Michigan State University.