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Productivity, market selection and corporate growth. Some comparative evidence.

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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 undertake two exercises. The first disentangle the two main processes through which incumbent firms contribute to the industry-level productivity growth, namely the within-firm productivity growth and the between-firms reallocation of shares. The evidence corroborates the notion that within-firm learning tends to play a more important role than competitive selection.

The second exercise addresses the relationship bewteen firm growth rates and productivity. The econometric analysis allows to take into account both the dynamic dimension of the selection process and idiosyncratic firm-specific factors. In this analysis, we measure the ``strength'' of reallocation by exploring if and to what extent firms growth rates are shaped by their relative productivities as compared to the industry means and by the variations in time of productivities themselves.

Rather surprisingly, we find that the latter turns out to be the dominant productivity-related determinant of relative growth rates.

Jelcodes:L11,D21

1 Introduction

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

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).

Evidence for 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.[2]

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 further question concerns the extent to which the relative productivity of a firm influences its growth rate. 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 evolutionary roots, which predict a relationship between the relative growth of a firm and its relative efficiency. The neoclassical perspective includes the models of Jovanovic (1982), Hopenhayn (1992) and Ericson and Pakes (1995) (for an extension to trade see Melitz, 2003). On the evolutionary side, formalitazions 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.

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

[2] An important caveat in all these studies is that they adopt different formulas to decompose productivity growth so that it is not simple to compare the results across countries in an homogeneous way. So, for example, Baldwin and Gu (2006) find, too, a negative between term in most sectors, when using the Griliches and Regev (1995) decomposition formula. The present study overcomes this shortcoming by providing a unique framework for such a comparison. See Foster et al. (2001) for a discussion of sensitivity of decomposition results to different methodologies.

Most of these theories predict that more productive firms should 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 firms growth rates. The main finding, there, is that the variance of growth rates is explained only to a little extent by the variance of relative productivities or profitabilites. The drawback of such econometric analysis, however, is that, by using standard fixed effect estimations, it washes away the contribution of a firm's average efficiency.

This paper builds on Bottazzi et al. (2010), but it attempts to disentagle, within a firm's fixed effect, the part which correlates with its productivity from the independent part. We start by presenting decompositions of productivity growth in four countries, namely USA, France, UK and Germany, in order to account for different institutional setups, plausibly influencing also the competition process. Next, we investigate the relationship between corporate productivity and growth, exploiting the panel dimension of our data.

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

2 Data and Variables

The present analysis draws upon two distinct datasets. For European firms, we use Amadeus, a commercial database provided by Bureau van Dijk. The edition at our disposal[3] contains informations from the balance sheet and the income statement account of over fourteen 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 among countries. Moreover, the yearly update drops all the firms for which there is no information in the last five years; as a consequence, coverage also varies by years. In order to have a set of countries and a time interval with a good coverage of variables of interest, we limit our sample to three countries, France, United Kingdom and Germany, with a slightly different span of years. For France and United Kingdom, we use data from 2000 to 2007. For Germany, the starting year is 2001.[4] For USA firms,

[3] i.e. March 2010.
[4] We also chose to leave out firms with less than 20 employees.

our source is COMPUSTAT, which contains data on listed companies. The time period covered goes from 2000 to 2007.

We are interested in corporate perfomances 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.

Firm growth is measured as the log difference of sales at constant prices, in two consecutive years.[5] The current values of the variables are deflated using production price indeces from EUROSTAT and from BLS.

We concentrate our analysis on manufacturing. Reported industries correspond to the 2-digits international ISIC Rev.4 classfication.

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 learn, innovate, imitate and thus improve the efficiency of their productive operations. This is what is often called the *within* component of productivity growth. On the other hand, incumbent firms may gain (or loose) market shares in favour or more (less) efficient firms. This is what is called the *between* component. The relative magnitude of the two components is a first evidence about market selection mechanisms. A bigger *within* component tells us 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 theese two components, we first define a general index of productivity for sector j as a weighted sum of individual firms' productivities:

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

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

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

where Δ is the difference between end and base year, and a bar over a variable indicates

[5] Figures on value added are directly available in Amadeus, while they need to be constructed in Compustat. We follow Brynjolfsson and Hitt (2003). Operating profits are computed as sales minus total costs. Cost of employees are obtained by multiplying the number of employees for the average sectoral cost of labour as reported by BLS at 4-Digits level of disaggregation.

the average of the variable over the two years. The two terms on the right hand side of the second equality sign identify the two components. The first term is the *within-firm* effect, i.e the productivity growth of firms weighted by their average shares while the second term is the *between-firms* effect, i.e. the variation in firms' shares weighted by average productivity levels.[6] 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

$$\sum_t \Delta\tilde{\Pi}_{j,t} = \sum_t \sum_{i\in j} \bar{s}_i \Delta\Pi_{i,t} + \sum_t \sum_{i\in j} \Delta s_{i,t}\bar{\Pi}_i \tag{1}$$

where the within and between components are the two terms of the sum.[7]

Two comments are in order about Equation (1). First, as by construction the sum of shares of incumbent firms (without entry and exit) is constant and equal to one, the between term captures to what extent 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 primarly compete in the goods market, and their expansion/contraction is revealed in terms of product shares, not employment shares. We will come back to the dynamics of firms' growth as measured by sales in the panel regression.

Table 1 presents the results obtained from decomposition as of Equation (1), according to sectors and countries. The most striking finding is the predominance of the within component in the great majority of sectors and the small values of the between component, a fact that holds irrespective of the country analyzed. The median of the between component is quite low everywhere: it is 6% in UK, 8% in USA, 10% in France, and strikingly -2% in Germany. Note that when the between term is negative as it is in quite a few sectors, that implies that shares in terms of employees are reallocated to *less* productive firms. Figure 1 offers a more intuitive picture of the decomposition exercise in the four countries by using violin plots. For each country, white violins refer to the share contribution of the between effect by sector and by country while shaded violins refer to the corresponding within share. It is apparent that the median value (the central line in each violin) of the two distributions are similar across countries, quite zero in the

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

[7]Notice 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	
	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

Decomposition based on Equation (1), over the period from 2000 (2001 for Germany) to 2007. Values are normalized as shares of total productivity growth.

bewteen case and near one in the within one. The small - and even negative - magnitude of the between component already witnesses against any simplistic view of the power of selection mechanism.

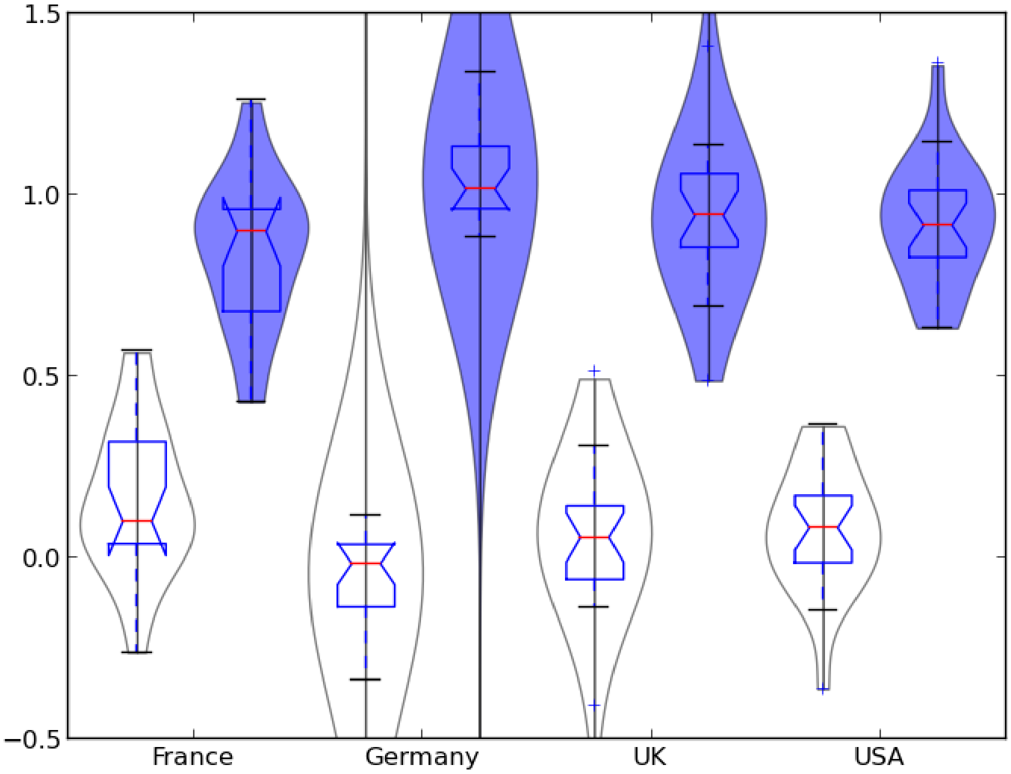

Figure 1: Distributions of *between* and *within* components across sectors.

Notes. Each violin plot is constitued by a box plot and a kernel density plot 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 have been calculated according to the values reported in table 1.

4 Regression analysis

So far, we have assessed the relative importance of firm-specific learning vs. selection/reallocation across firms as 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. 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 productivity (relative to the other firms in the same industry) in a regression framework. 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 as the key potential driver of firms' changing market shares and growth. In the latter, instead, we consider the impact of variations of productivity - its relative growth rates - upon corporate growth.

We measure 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 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

$$g_{i,t} = a + b_t + \sum_{l=0}^{L} \beta_l \pi_{i,t-l} + u_i + \epsilon_{i,t} \tag{2}$$

where $g_{i,t}$ denotes the growth rate of firm i in terms of log-differences of sales between two consecutive years, $\pi_{i,t}$ the (log) labour productivity, b_t is a time dummy, $l = 0, ...L$, with L the longest lag length considered, u_i is a firm-specific time invariant unobserved effect, and $\epsilon_{i,t}$ is an 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.[8]

Simple selection criteria based on the $t-$statistic led us to choose as baseline equation the one with $L = 1$:

$$g_{i,t} = a + b_t + \beta_0 \pi_{i,t} + \beta_1 \pi_{i,t-1} + u_i + \epsilon_{i,t} \tag{3}$$

Results from fixed effect estimation of equation (3) are shown in table 2. In almost the totality of sectors across the four countries, coefficients β_0 and β_1 are significant at the 1% level. This result seems to suggest that the level of productivity, both at time t and at time $t-1$, has an effect on a firm's growth rate and that the effect is robust both to sector and to country specificity.

As for the sign and the magnitude of the coefficients, a strong regularity emerges, which is apparent from the graphical representation of the results plotted in figure 2, displaying, for each country, two shaded violin plots, which represent the distribution of the sectoral coefficients β_0 (the leftmost violin) and β_1 (the rightmost violin), and in the middle a white violin, which represents the sum of the two coefficients. The two coefficients are quite stable in absolute value, with a median across sectors of about 0.2

[8]The 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 ($E(\epsilon_{i,t}|\mathbf{x_i}, u_i) = 0$) also requires that future values of the dependent variable are uncorrelated with present shocks. We tested this hypothesis by including x_{t+1} in our regressions. The coefficients of this variable were not statistically significant in the large majority of the cases.

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

Note. Fixed effect estimation with standard error in parenthesis. The dependent variable is the firm's growth rate as proxied by the log difference of sales between two consecutive years. ^{a} $p < 0.01$, ^{b} $p < 0.05$, ^{c} $p < 0.10$.

in all the four 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 violines, all tightly spread around a median value of about zero.

These results suggest two main conclusions. Firstly, the effect of the level of productivity is ambiguous: positive at time t and negative at time $t-1$. Secondly, this ambiguity would disappear if one looked at the effect of the productivity's growth rate, $\pi_{i,t} - \pi_{i,t-1}$,

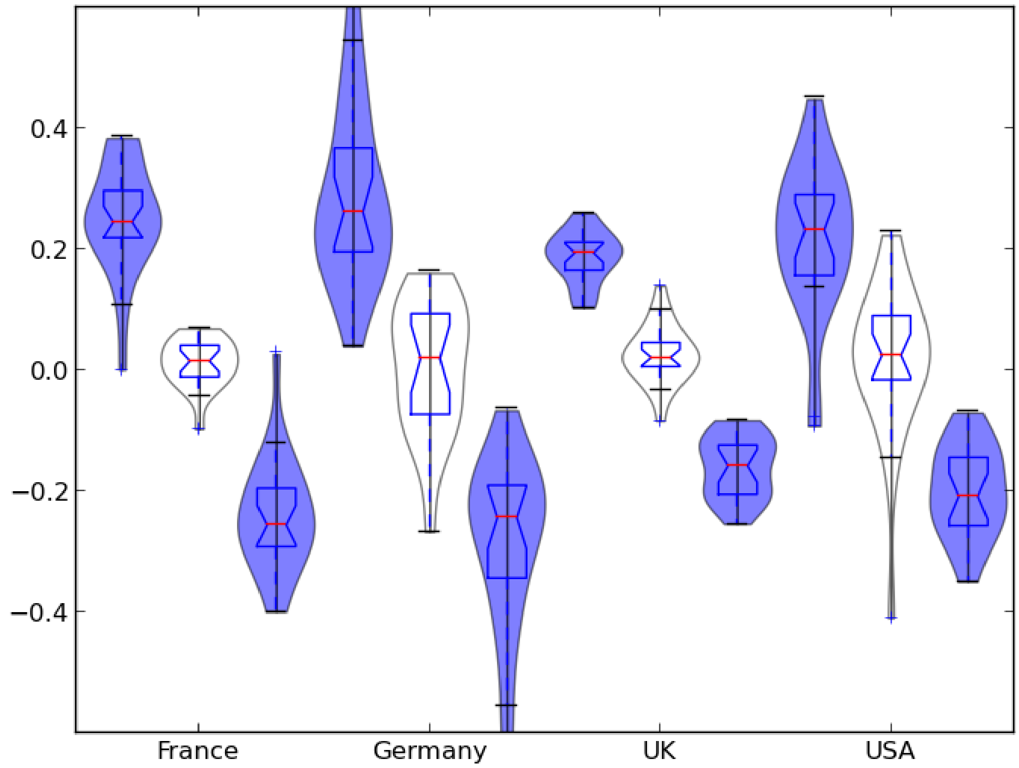

Figure 2: Distributions of β_0, β_1 and $\beta_0 + \beta_1$ across sectors.

Notes. 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 have been calculated according to the values reported in table 2.

which is positive on average. We will come back to this point below.

4.2 The explanatory power of productivity

The estimates of β_0 and β_1 from Equation (3) stand for elasticities: a 1% increase in productivity at time t or $t-1$ is related to an average increase in sales growth of about 0.2. However, even if these are dimensionless quantities, they are not able to pinpoint the "strength" of the linear association between the two variables, and thus they do not say much on the extent to which firms are selected according to their relative productivity. In order to assess it, we need to resort to a coefficient of determination, measuring the variance of $g_{i,t}$ explained by $\pi_{i,t}$ (and $\pi_{i,t-1}$). This is what one does in Bottazzi et al. (2010) (just with respect to $\pi_{i,t}$, admittedly not necessarily satisfying exogeneity conditions): the estimates on France and Italy suggest that only below a quarter of explained variance comes from productivity "alone", while the contribution of the unobserved heterogeneity (the "fixed effect") is much larger, so that productivity differentials appear to "explain" roughly between 3% and 5% of the overall variance in growth rates.

Here, the dynamic specification of equation (3) ensures that exogeneity conditions are met so that standard within-group estimation gives unbiased coefficients. However, estimate (3) systematically neglect the "productivity 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 need to do is to disentangle, within the unobserved effect u_i, the part which is correlated with productivity from the part which is not. In order to do so, we re-estimate equation (3) by applying the correlated random effect model. This implies standard random effect estimation of the following equation

$$g_{i,t} = a + b_t + \beta_0\pi_{i,t} + \beta_1\pi_{i,t-1} + \beta_{0a}\bar{\pi}_i + \beta_{1a}\bar{\pi}_{i,-1} + c_i + \epsilon_{i,t} \tag{4}$$

where $\bar{\pi}_i$ and $\bar{\pi}_{i,-1}$ are the time series averages of the (log) productivity up to time t and $t-1$, respectively, and c_i is the new unobserved firm-specific heterogeneity term, uncorrelated with the regressors after controlling for their averages. The advantage with respect to Equation (3) is that we are explicitly taking into account the contribution to sales growth also of productivity averages through time.[9]

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

[9]Note that random effects estimation of equation (4) does not change the value of the coefficients β_0 and β_1.Indeed, as shown in Mundlak (1978) for the balanced panels and Wooldridge (2009) for the unbalanced ones, coefficients obtained from a fixed effect estimation are equal to the corresponding coefficients obtained from a random effect estimation of the same equation augmented with the time averages of the regressors.

$$S^2 = \frac{Var(\beta_0 \pi_{i,t} + \beta_1 \pi_{i,t-1} + \beta_{0a} \bar{\pi}_i + \beta_{1a} \bar{\pi}_{i,-1})}{Var(g_{i,t})} \quad . \tag{5}$$

The traditional coefficient of determination, R^2, takes into account the contribution of the heterogeneity term c_i

$$R^2 = \frac{Var(\beta_0 \pi_{i,t} + \beta_1 \pi_{i,t-1} + \beta_{0a} \bar{\pi}_i + \beta_{1a} \bar{\pi}_{i,-1}) + Var(c_i)}{Var(g_{i,t})} \tag{6}$$

so that the difference between R^2 and S^2 delivers a measure of the variance explained by time invariant unobserved factors.[10]

Table 3 reports the values of S^2 and R^2 across industries and by country. Values of R^2 show that a simple linear model with productivity and firm-level heterogeneity is able to account for around 40% and 65% of the variance in the firms' growth rate (median values across sectors are 0.41 for France, 0.66 for Germany, 0.39 for UK and 0.51 for USA). The values of S^2, capturing only the contribution of the productivity terms (both levels and averages), are smaller, meaning that fixed "idiosyncratic" effects continue to be at work even if with a smaller contribution to the overall explained variance as compared to Bottazzi et al. (2010). Still, they represents non negligible values as compared to the R^2. Median values of S^2 are 0.19 for France, 0.18 for Germany, 0.14 and 0.15 for USA: that is, productivity differentials account for between one fifth and one sixth of the variance in firms' growth rates. However, there is something paradoxical in this result, in the sense that productivity enters statistical with the positive sign with the contemporaneous variable and negative with the lagged one. Let us address the puzzle.

[10] More precisely, R^2 also includes the contribution of time dummies. In our case, these turned out to account for a negligible amount of the variation in the dependent variable so we omit them.

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 effect estimation of equation (4).

4.3 Productivity levels and productivity variations

The puzzle of the apparent explanatory power of productivity as measured by the S^2, in contrast with the results of the decomposition exercise, in which the values of the between component did not signal any relevant selection effect at work, is in fact statistically resolved by looking at the dynamic structure of the regression analysis. The analysis of 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 $t-1$, - widespread across sectors and countries -, suggests that the actual drivers of firm growth do not seem to rest in the relative *level* of productivity at any time period, but in their *variation* through time.

To test this conjecture, we need to divide the S^2 of productivity in two components, related respectively to levels and variations over time. Rewrite equation (3) as

$$g_{i,t} = a + b_t + \beta_\Delta \Delta\pi_{i,t} + \beta_m \bar{\pi}_{i,t} + u_i + \epsilon_{i,t} \tag{7}$$

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 of productivity level over t and $t-1$, which captures the absolute differential efficiency among firms.[11] Under the hypothesis that firms are selected and grow mostly according to their "static" relatively 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 productivity growth rates, the explanatory power of $\Delta\pi_{i,t}$ should dominate.

We first estimate with random effect the equation

$$y_{i,t} = a + b_t + \beta_\Delta \Delta\pi_{i,t} + \beta_m \bar{\pi}_{i,t} + \beta_{\Delta a} \bar{\Delta\pi}_i + \beta_{ma} \bar{\bar{\pi}}_{i,t} + c_i + \epsilon_{i,t} \tag{8}$$

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 (5).[12]

Results are reported in Table 4 while a graphical representation is offered in Figure 3. The value of $S^2_{\bar{\pi}_{i,t}}$, i.e. the fraction of growth rate variance accounted for by producitivity levels, is very close to 0 in basically all sectors, irrespectively of the country considered. Correspondingly, the values of $S^2_{\Delta\pi_{i,t}}$ are always nearly identical to the values of the S^2 reported in Table 3. We can thus conclude that the extent of the explanatory power of productivity with respect to firm (sales) growth entirely stems from *variations* in efficiency more than from absolute differentials of productivity levels across firms. This conclusion is also in line with what was found in the decomposition exercise: the between component

[11] Notice that β_Δ and β_m are related to the coefficients of equation (3) through $\beta_0 = \frac{\beta_m}{2} + \beta_\Delta$ and $\beta_1 = \frac{\beta_m}{2} - \beta_\Delta$.

[12] When separating out the effect of $\Delta\pi_{i,t}$ from that of $\bar{\pi}_{i,t}$ we assign the covariance terms in equal part to each of the two components.

of aggregate industry productivity did not signal any relevant role of selection effects, as obviously measured in terms of relative productivity levels. Significants, even if relatively small effects of reallocation and market selection among firms, can only be detected in terms of *relative dynamics* in efficiencies.

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 effect estimation of equation (8).

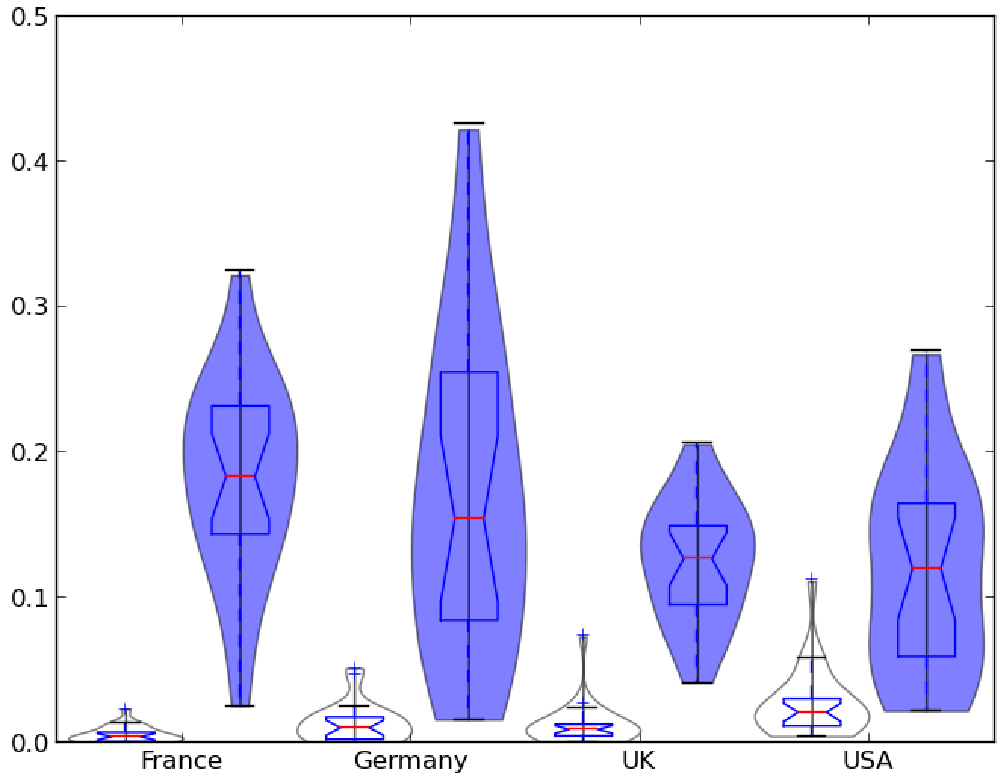

Figure 3: Distributions of $S^2_{\Delta\pi_{i,t}}$ and $S^2_{\bar{\pi}_{i,t}}$ across sectors.

Notes. 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 have been calculated according to the values reported in table 4.

5 Conclusions

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

The first proposed exercise supports the claim 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 overall productivity dynamics.

Focussing more directly at the relation between relative efficiency levels and relative growth rates seems to suggest, at a first look, a much stronger relation between past and presente productivity levels and growth. However, this is largely a statistical artifact, due to a significant non-negligible positive coefficient on the contemporaneous productivity variable and a quite similar negative coefficient on the lagged one. In a more economically meaningful way, if one takes the differences over time - that is the *rates of productivity growth* - one finds a significant effect on relative corporate growth, even if modest in terms of explanation of the overall variance in growth rates.

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 foregoing evidence seems to suggest 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 example, the car industry is composed of different segments, whereby Fiat 500’s do not compete with Audi’s which do not compete with Ferrari’s. And of course each sub-market is characterized by different average productivities, in addition of course to different product characteristics. As an illustration it is useful to resort to 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”. In each of three submarkets it is plausible to think of a relation relative productivity-relative fitness-relative growth of a sort of replicator-type. However,

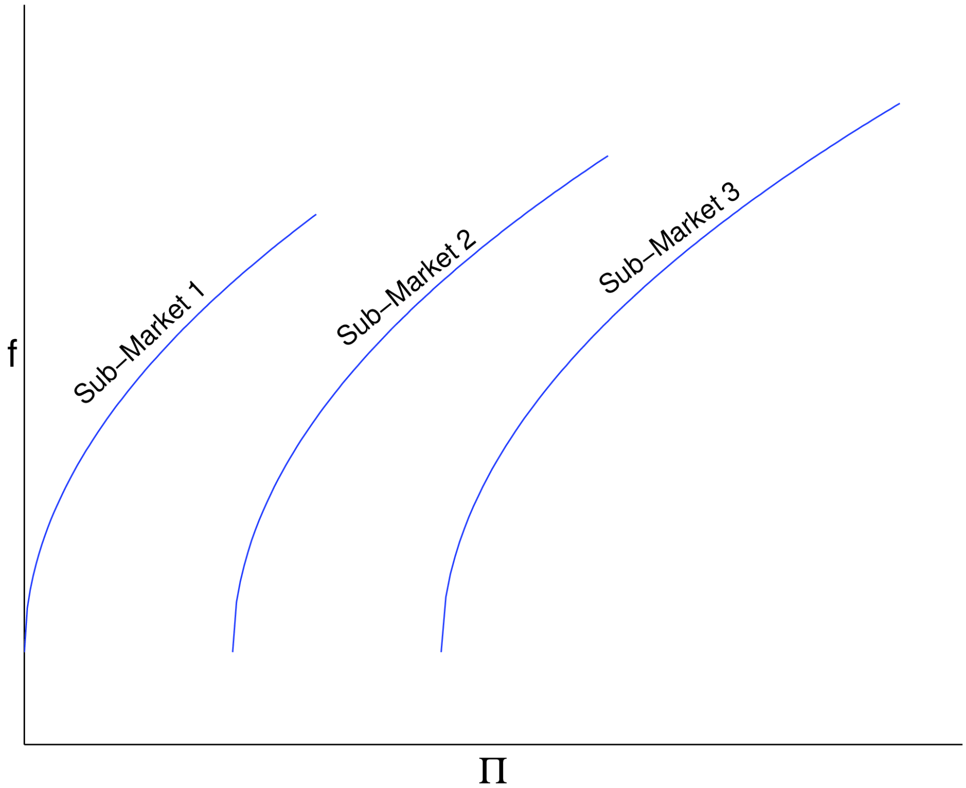

Figure 4: Submarkets landscape.

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. However, note the following: within each submarket any improvement in productivity leads, other things being equal, an improvement in “fitness”. And this is precisely what our 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.

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