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What does (or does not) determine persistent corporate high-growth?

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outstanding growth performance. Is the same conceptual framework a convincing explanation to account for persistent corporate high growth? Exploiting panels of Italian, Spanish, and French firms we find no evidence that this is the case: companies experiencing persistent high growth are not more productive nor more profitable, and do not display peculiarly sounder financial conditions than firms that only exhibit high, but not persistent, growth performance. The finding is robust across countries, across sectors displaying different innovation patterns, and also controlling for demographic characteristics such as age and size.

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WORKING PAPER SERIES

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What does (or does not) determine persistent corporate high-growth ?

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Abstract

Theoretical and empirical studies of industry dynamics have extensively focused on the process of growth. Theory predicts that production efficiency, profitability and financial status are central channels through which some firms can survive, grow and eventually achieve outstanding growth performance. Is the same conceptual framework a convincing explanation to account for persistent corporate high growth? Exploiting panels of Italian, Spanish, and French firms we find no evidence that this is the case: companies experiencing persistent high growth are not more productive nor more profitable, and do not display peculiarly sounder financial conditions than firms that only exhibit high, but not persistent, growth performance. The finding is robust across countries, across sectors displaying different innovation patterns, and also controlling for demographic characteristics such as age and size.

JEL codes: D22, D24, L26

Keywords: High-growth firms, Persistent high-growth, Productivity, Firm age, Firm size

1 Introduction

Among the many private companies that populate developed economies it is typically possible to identify a small group of firms with extraordinary growth performance, which are commonly referred to as high-growth firms or "gazelles" (among others, see Schreyer, 2000; Delmar et al., 2003; Acs and Mueller, 2008; Parker et al., 2010). This kind of companies attracts the attention not only of academic scholars, but also of managers, practitioners and policy makers (see for instance the discussion in Schimke and Mitusch, 2011). On the one hand, managers and consultants seek to understand the "best-practices" which are responsible of superior performance and try to replicate them within their own business or the business of their clients. On the other hand, policy-makers are particularly interested in the early identification of high-growth firms because of their extraordinary potential in terms of new jobs creation. We observe indeed a raising number of initiatives, especially in the EU, targeting the emergence of such companies.

There is a vast literature, mostly empirical, on high-growth companies, that links high-growth to both macro-economic or institutional factors, external to the firm, and to micro-economic characteristics specific to a given firm. The latter often include demographic variables such as age and size, together with more economic determinants such as firm innovativeness. This literature is mainly focused on the identification of the causes and conditions that led a company to outperform its competitors in a specific, relatively short, period of time (see the short review in Section 2)

In this paper we offer a different perspective. Instead of searching for the reasons that make a firm a high-growth firm at a given point in time, we want to identify the factors that make it a *persistently* high-growing firm. The justification for this shift of focus is straightforward: extraordinary high growth performances have a more relevant economic impact and turns more interesting to practitioners and promising to policy makers, if they are long lasting and persistent. This is indeed the kind of grow behavior that is likely connected with the presence of exceptional capabilities inside the firm or structural advantages around it. As a matter of fact, the dynamics underlying a fast expansion can vary, even in substantial form, from company to company (Delmar et al., 2003): some entities sporadically respond to market shocks, some companies display a more erratic and unpredictable pattern, and only few are able to exhibit a persistent, continuing year after year, fast expansion.

While empirical research has for long concentrated on persistence of firm growth rates, with mixed results, the study of persistence of high-growth patterns is only of very recent development. Moreover the few existing studies (Coad, 2007; Coad and Hölzl, 2009; Capasso et al., 2013; Hölzl, 2014) limit their attention to mere demographic characteristics, such as size, age or sector of activity. We instead address whether persistent high-growth firms differ in terms of more structural characteristics and performances with respect to firms that display “spurs” of high growth, but are yet not able to consistently sustain high growth rates over longer periods of time. We do not know of previous studies making an attempt in this direction.

The existing theories of firm-industry dynamics with heterogeneous firms, which stems from different traditions (see, e.g., Nelson and Winter, 1982; Jovanovic, 1982; Silverberg et al., 1988; Dosi et al., 1995; Metcalfe, 1998; Ericson and Pakes, 1995; Cooley and Quadrini, 2001; Luttmer, 2007) provide the theoretical background of our analysis. Although none of these models specifically addresses the issue of the relative abundance of high-growth firms and their behavior over time, they all share a common set of hypotheses, and often a common core of predictions, which are strictly related to our investigation. First, the key driving forces of firm growth are productivity (as a summary measure of idiosyncratic characteristics like managerial, organizational and innovation or knowledge-related capabilities), profitability and financial conditions. Second, these three key dimensions are strongly related: higher efficiency firms grow more and gain market shares, either directly via lower prices, or indirectly via increasing profits which, in combination with superior financial performance, allow them to invest and pursue further growth, especially in presence of financial market imperfections. Hence we should expect high-growth firms to be more productive, more profitable and financially more solid. Third, these models relate growth rates differentials across firms to the presence of competitive advantages due to structural factors which influence firm performances over a relative long period of time. Thus, they provide hints about the degree of persistence one should observe in firm’s growth: due to the presence of market imperfection or institutional frictions, the “good firms”, i.e. innovative entrants or successful incumbents, tend to expand toward their optimal size at first rapidly and then experiencing a progressive slow down. The mechanism behind the growth slow down can be both static, due for instance to non linearity of production costs or demand factors, or dynamic, as related with internal organization and (the lack of) managerial competences (c.f. the huge literature on dynamic capabilities in the Chandlerian tradition from the early Penrose (1995) to the recent Katkalo et al. (2010)). In any case, these models tend to suggest that the over-performing trend is not immediately reabsorbed so that one expects to observe a positive relation between competitiveness and persistent high growth. Conversely, isolated high growth events can be simply the effect of exogenous demand and price shocks.

Our analysis proceeds as follows. Exploiting panel data on Italian, French and Spanish manufacturing incumbents, we identify high-growth companies, and within this group, those displaying persistent high-growth. It turns out that only a very small proportion of firms sustain their superior growth performance over time. We then analyze how initial years productivity, profitability and financial factors relate with subsequent growth dynamics. We perform both a non-parametric and parametric analysis. First, we explore if a set of key variables, taken to proxy the operational performance and financial status, display distributional differences across high growers, persistently high growers and other firms. Second, we estimate discrete choice models to identify which variables are more effective in discriminating persistent high-growth firms from "simple" high-growth and other firms.

Our findings are challenging for both academics and policy makers. Indeed, we do confirm that economic determinants, and productivity in particular, is strongly associated with high growth. However, we do not find evidence of any statistically significant difference between high-growth and persistent high-growth firms. None of the considered dimensions therefore seems to work in sustaining high-growth performance repeatedly over time. The same pattern is invariant across countries, suggesting a minor role for institutional or other more macro-level factors. Further, the picture is robust to a number of extensions, including controls for sectoral patterns of innovation and demographic characteristics such as size and age.

The next Section 2 presents the related literature. In Section 3 we provide the empirical framework, describing the identification of high-growth and persistent high-growth companies, and the empirical methods adopted in the analysis. Section 5 discusses our main results, while robustness checks are reported in Section 6. We conclude in Section 7.

2 Background literature

Our study is directly related to the empirical literature concerned with the identification and characterization of high-growth companies. The basic "stylized facts" emerge from the seminal study by Schreyer (2000). Based on firm-level data from five OECD countries (Germany, Italy, Netherlands, Spain and Sweden) as well as from Quebec (Canada), high-growth firms are found to be (i) present in all industries and in all regions of the examined countries; (ii) more R&D intensive than "normally growing" firms or than the average incumbent; (iii) younger and smaller than the average firm. Consistent results have been confirmed by subsequent studies.

Concerning the determinants of observed high growth, a stream of literature focused on the role of factors external to the firm, such as institutions, geography, sectoral or broadly speaking macro-level characteristics. Among others, Davidsson and Henrekson (2002) investigate the importance of a number of institutions and policy measures such as taxation of entrepreneurial income, incentives for wealth accumulation, wage-setting and labor market regulations. The evidence, from a panel of Swedish firms, shows that the little support to dynamic firms by policy makers can hinder nascent entrepreneurship and the net employment contribution by high-growth firms. Acs and Mueller (2008) stress the role of local knowledge spillover as a driver of firm's birth rate and high-growth, concluding that metropolitan areas offer fertile ground for fast growing firms, whereas small cities facilitate new entry but not the expansion of rapidly growing units.

More recently, scholars have started to look at more micro-level determinants of high growth, in particular focusing on innovation-related drivers. Coad and Rao (2008) link innovation to sales growth of incumbent firms in high-tech sectors, finding that innovation is of crucial importance only for a handful of high-growth firms. Hölzl (2009) explores the relationship between R&D and superior growth performance using CIS III data for 16 countries. His findings reveal that R&D is more important to high-growth firms in countries that are closer to the technological frontier, suggesting that high-growth firms derive much of their drive from the exploitation of comparative advantages rather than from other firm-level determinants. Segarra and Teruel (2014) show, on Spanish data, that R&D investment positively affects the probability to be a high-growth firm, but internal and external R&D have asymmetric effects on the firm growth rates distribution, with internal R&D being the only type of investment having a positive impact among high-growth firms. Finally, Colombelli et al. (2014) investigate the innovation strategies of a set of European publicly traded companies by building specific indicators of the structure of knowledge (i.e. variety, coherence, and similarity). The evidence supports the idea that high-growth firms tend to adopt exploration rather exploitation strategies, therefore stimulating the creation of new technological knowledge.

As the influential contribution by Delmar et al. (2003) has highlighted, however, high-growth firms do not all grow in the same way, and results can be sensitive to alternative size-growth proxies as well as to alternative criteria to identify high growth. The study identifies seven different types of firm growth patterns, in turn different in terms of demographic characteristics such as size, industry affiliation, firm age, and type of governance. Differences are sharp, ranging from "super absolute growers", dominated by small- and medium-sized firms operating in knowledge intensive manufacturing industries, to the "erratic one-shot growers", dominated by small-sized firms in low-technology service sectors. It is then plausible to expect that, according to the definition of high growth which is adopted, the investigation of its determinant can lead to different results. This consideration motivate us to adopt a multidimensional measurement criterion and to embark into a series of robustness checks with respect to possibly alternative criteria. Moreover, with respect to the studies cited above, essentially focused on the explanatory factors of possibly short-run and sporadic high growth events, we also want to include the persistence of such high-growth dynamics into the analysis. In this respect it is useful to take a step back and refer more closely to what existing theories suggest us to look at in the search for the drivers of high growth.

We draw our theoretical background from models of firm-industry evolution with heterogeneous firms, originally developed within the evolutionary disequilibrium approach with no anticipating or strategic agents (see, e.g., Nelson and Winter, 1982; Silverberg et al., 1988; Dosi et al., 1995; Metcalfe, 1998), and revisited within a more standard partial equilibrium frameworks with (possibly bounded) rational agents and strategic interaction (such as in Jovanovic, 1982; Hopenhayn, 1992; Ericson and Pakes, 1995; Cooley and Quadrini, 2001; Melitz, 2003; Asplund and Nocke, 2006; Luttmer, 2007). Despite differences in the core assumptions from alternative schools of thought, these models share a common mechanism of firm selection and growth, which is made explicit in disequilibrium dynamical models and is implicitly described as the convergence to the equilibrium path in equilibrium models. The predicted pattern starts typically with an idiosyncratic shock to incumbent firms, or with an idiosyncratic initial endowment of entrants, as the first driver. The shock regards firm-specific unobserved factors, such as technological and organizational traits, capabilities, strategic and managerial practices, and it gets reflected into heterogeneous efficiency across firms. Next, firms with higher relative efficiency grow and gain market shares at the expenses of less efficient units, either directly via lower prices, or indirectly via increasing profits which, in combination with sounder financial performance, grant to more productive firms the access to the resources needed to invest and pursue further growth, possibly with some time lag.

Although these models are not directly concerned with high-growth performance, relevant for our study are the implications in terms of the characterization of high-growth companies. First, the framework predicts that the candidate key drivers of high growth must be searched for in terms of efficiency, profitability and finance-related factors. Second, we should expect that high-growth firms are more productive, more profitable and display sounder financial conditions than other firms.

Less clear-cut from the models is whether the same firm characteristics can be also seen as the drivers of persistent high growth performance. Some scholars have even advanced the hypothesis that randomness (or "mere luck") is the most appropriate account of firms' persistent success (Barney, 1997). The empirical literature on persistence of firm growth does not help in this respect. A huge amount of work has been devoted to detect an autocorrelation structure in the growth process as a way to test Gibrat's Law. The results are mixed, ranging from the view that growth is indeed a random walk advanced in Geroski (2002), to the evidence of strong autocorrelation (up to the 7^{th} lag) found in Bottazzi et al. (2001). In between, positive serial autocorrelation is found by Geroski et al. (1997) on a panel of UK quoted firms, Wagner (1992) on German manufacturing companies, Weiss (1998) on the Austrian farm sector, and Bottazzi and Secchi (2003) on US manufacturing firms, while negative serial correlation is found, for instance, by Goddard et al. (2002) on Japanese quoted firms, and by Bottazzi et al. (2007) and Bottazzi et al. (2011) for Italian and French manufacturing, respectively.[1] More recent studies adopt different statistical techniques (i.e. quantile autoregression and transition probabilities matrix) to consider the entire distribution of the growth rates. Coad (2007) and Coad and Hölzl (2009) do observe some degree of persistence, with small high-growth firms displaying negative autocorrelation whereas large and established companies achieving smoother dynamics. On the contrary Capasso et al. (2013) conclude by arguing that the existence of persistent outperformers is especially pronounced in micro firms. Hölzl (2014), while still confirming that most of high-growth firms are not able to replicate their high-growth event over time, prove that the degree of persistence might however depend upon the type of criterion adopted for the identification of such companies.

Overall, none of these studies address if more structural, economic or financial, factors beyond and above demographic characteristics such as size, age, and industry affiliation, are distinguishing features of persistent high-growth companies and work effectively in driving the underlying persistent high-growth patterns.

3 Empirical framework

Models of firm-industry evolution predict that market competition should favor more efficient and profitable firms, and that sounder financial conditions should help accessing the external resources needed to finance invest-

[1] Findings on service firms provide a similarly mixed picture, as in Vennet (2001) on banking companies across OECD countries and Goddard et al. (2004) on US financial services.

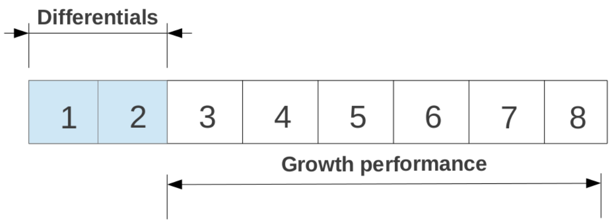

Figure 1: Partitioning criterion: first and second time span

ment and growth. Hence, we should expect high growth firms to be more productive, more profitable, and financially more solid than firms displaying "less abnormal" growth. Is this the case in the data? And moreover, do the same firm characteristics also display any association with persistence in high growth? More specifically, do, and if so to what extent, persistent high-growth companies differ with respect to other firms, and in particular with respect to other high growth firms?

In this section we describe the empirical framework we adopt to address the above questions. A key point is that the identification of persistence in high-growth performance requires a reasonably long period of time over which evaluating firm growth. Our strategy is to divide the time span available in the data into two periods, and exploit the firs period to measure "initial" firm characteristics, which we next seek to map into high-growth, persistent high-growth or "normal" growth performance measured over the second period.

Identifying high-growth and persistent high-growth firms

The first obvious step in the analysis is to choose, first, a definition of high-growth (HG) firms and, second, a strategy to identify persistent high-growth (PHG) performances. There are no commonly accepted identification criteria in the literature, due to the quite disparate approaches followed in previous studies. In fact, studies on high-growth companies consider a long list of alternative size-growth indicators such as assets, employment, market share, physical output, profits or sales. Moreover, there is a variety of possible criteria to classify a firm as high-growth, once a given indicator is chosen. At the same time, studies looking at persistence of growth focus on the degree of autocorrelation in the sectoral growth rates distributions (average or within quantiles), but do not provide a criterion to identify persistent high-growth enterprises, beyond sharing the obvious idea that these firms must be those experiencing high-growth performance – however defined – consecutively for some years.

Against this background, we implement the following choices. First, we measure annual growth g_{it} of firm i at time i in terms of the log difference

$$g_{it} = s_{it} - s_{i,t-1} \quad , \tag{1}$$

where

$$s_{it} = log(S_{it}) - \frac{1}{N}\sum_{i} log(S_{it}) \quad . \tag{2}$$

and S_{it} is either the sales (annual turnover) or the number of employees. In this way the growth rates are normalized by their annual sectoral average. The normalization implicitly removes common trends, such as inflation and business cycles effects in sectoral demand.

Given a sample period of 8 years, we measure growth patterns over the last six years, while we reserve the first two years to evaluate other firm characteristics that we want to map into growth performance (see Figure 1).

Second, to identify high-growth firms, we compute the time-series average of the annual growth rates computed over the six years spanning the second part of the sample period, and then define as high-growth firms those companies lying in the top 10% in terms of at least one growth measure, i.e. either growth of sales or growth of number of employees (or both).

Finally, to define persistent high-growth firms, we examine, again over the last six years of the sample period, the annual growth rates of the high-growth firms identified in the previous step, and then define the sub-sample of persistent high-growth companies as those firms belonging for at least four years to the top 10% of the yearly cross-sectional distribution of either sales or employment growth (or both).

Through the above identification criteria we end up with three categories of firms experiencing distinct "growth status": high-growth (HG) firms, persistent high-growth (PHG) firms, and the rest of the sample, which from now on we refer to as "other firms" (see Figure 2).

The choice to consider both sales and employment growth in the definition of HG and PHG firms responds to the idea advanced in the literature that no single "best" indicator of size exists, with each alternative proxy measuring different aspects of the firm growth process. By considering simultaneously sales and employment growth, we seek to provide a multidimensional view on the growth process. Indeed, sales is more a proxy of success on the market, while employment is more related to establishing capacity.[2] At the same

[2]Also notice that sales and employment are indeed the most frequently chosen size proxies in the literature, mainly for practical reasons. They are relatively easily accessible, they can be compared within and between industries (for instance physical output do not benefit of the same property), and they are not too much related to the capital intensity

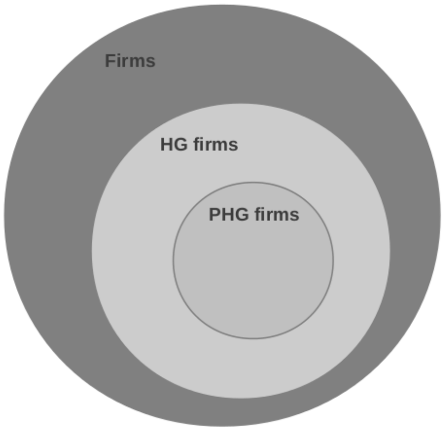

Figure 2: Three categories after the identification and selection step

time, defining HG and PHG firms based on a single size indicator can in principle considerably reduce the sample size of the two groups of firms, in turn leaving too few observations to perform meaningful empirical analysis. We have however verified that our main empirical findings do not change if we identify HG and PHG firms based on separate criteria on employment or sales growth.

The strategy to impose a threshold on average annual growth in defining HG firms is in line with the vast majority of previous studies. The number of years considered as well as the precise threshold may vary across studies, but the main idea is common to all studies. There is instead less consensus on whether the threshold must be an absolute value (for instance defining as an HG firm a firm that hires at least 100 employees) or in relative terms, that is looking at percentage growth over time. We follow this second approach. Using absolute growth would imply a bias towards larger firms, whereas the percentage measure also allow for smaller firms to enter the HG group. More questionable is the imposition of the top 10% threshold on annualized average growth. We have therefore experimented both with less and more restrictive definitions (consider 15 or 5 %), but the main conclusions from the empirical analysis remain valid.

The definition of PHG is less grounded on previous research, given the already mentioned lack of attention in defining these type of firms. The criterion we propose tries to balance between the need to actually capture firms that do outperform for a reasonably long period of time and the time

of the industry (as opposed to total assets). Notice that the inter-sectoral comparability is improved by the use of the normalized shares defined in (2) constraints imposed by the data. Persistence is indeed a relatively rare phenomenon, so that imposing too restrictive criteria can dramatically reduce the sample of identified PHG firms, making the empirical analysis unfeasible. We have anyhow experimented with different thresholds (including. e.g., the top 15% or the top 5%) and with a more restrictive identification imposing a longer HG status (5 instead of 4 years). The results presented in the following empirical analysis are robust to these alternative criteria.[3]

Methodology

Two types of statistical analysis are performed to identify the association between growth performance and initial economic and financial factors.

First, we perform a comparison of the empirical distributions of initial firm characteristics across the three groups of HG, PHG and "other firms". For this purpose, we compute the average firm-level productivity, profitability and financial performance over the two initial years which are not used to identify HG and PHG patterns, and apply different tests of distributional equality across HG, PHG and "other firms". We start with a simple two-sample Student's t test for equality of the mean across samples with unequal variances. The test is aimed to assess whether the sample means of the three groups are equal. This test is powerful when the samples to be compared are small (as in our case), but it rests on normality assumption, which is often violated when dealing with firm-level variables. We thus turn to non-parametric tests, which can have the drawback to require more data to achieve a similar power, but on the other hand do not assume normality across the compared samples. First we consider the Wilcoxon-Mann-Whitney test (hereafter, WMW) for the difference in medians between two similarly shaped populations. This test has the advantage to account for asymmetries in the statistical distributions. We then apply the Fligner and Policello (1981) procedure (hereafter, FP) allowing to asses the stochastic equality of the compared distributions. That is, instead of assuming that the compared samples only differ for a shift of location (in mean or median), the FP test look at the stochastic dominance between two compared samples. The FP test is the most robust among our alternatives. In fact it makes the least restrictive assumptions: it can be applied on uneven samples, as it is likely to be the case with our data, given the quite unequal number of firms falling into the three growth categories, it does not require equality of variances, and it allows for asymmetries.

[3] Detailed results for the alternative specifications are available upon request. Further details on the sample are presented in the data Section below.

In the second part of the empirical analysis, we adopt a more standard regression approach, investigating the role of firm characteristics in predicting the probability that a firm belongs to the three groups of HG, PHG and "other firms". The dependent variable is a multiple discrete choice indicator:

$$y_i = \begin{cases} 0 & \text{if firm } i \text{ is "other firms"}, \\ 1 & \text{if firm } i \text{ is HG firms}, \\ 2 & \text{if firm } i \text{ is PHG firms}, \end{cases} \tag{3}$$

defining the observed growth status in period II. The probability to belong to each category is then modeled as a function of a vector $\mathbf{v}_i$ of explanatory variables:

$$P_j := Pr[y_i = j|\mathbf{v}_i] = F(\beta_j'\mathbf{v}_i) \ , \tag{4}$$

including the average values of firm-level productivity, profitability and financial indicators computed over the two initial years of period I, with $\beta_j, (j = 0, 1, 2)$ the coefficient to be estimated corresponding to each firm characteristic.

Since the growth status is unordered (we might have inverted the assignments without any effect) and, by construction of the three groups, we cannot hold the independence from irrelevant alternatives assumption required by Logit-type of estimators, we estimate the model in (4) through a Multinomial Probit, via full maximum likelihood. Despite some computational burden related to the underlying specification of a multivariate Normal distribution, the outcomes of the estimation are simple to interpret as the multiple choice version of a usual binary choice Probit, once a baseline category is chosen. The lag between growth status (measured in the second time span) and initial firm characteristics (measured in the first time span) reduces potential endogeneity of regressors.

The next section discusses the empirical proxies for the main firm characteristics entering the analysis, together with a general presentation of the dataset and of the samples of HG and PHG firms.

4 Data, variables and descriptive statistics

The present study draws upon firm-level information from the AMADEUS dataset, a well known and widely used commercial database provided by Bureau van Dijk. AMADEUS contains detailed balance sheet and income statement information for firms active in all sector of activity, covering all European countries. We have access to data on Italy, Spain and France firms. The edition at our disposal (2012) covers a time span of 9 years, from

2004 to 2012. However, to have a time interval with a good coverage of the variables of interest in all countries, our analysis spans the period 2004-2011. In line with previous studies (among the many, see Schreyer, 2000; Delmar et al., 2003; Coad, 2009; Bottazzi et al., 2011), our attention is on *continuing incumbent firms*: firms that entered midway after 2004 or exited midway before 2011 have been removed, yielding a balanced panel over the sample time window. Further, our main concern is about internal growth, and we therefore exclude those firms who experience any kind of modification of structure, such as mergers or acquisitions. The survival bias that this selection procedure might possibly introduce is minimal in this case as we will run a comparative analysis across different groups of surviving firms.[4] All the firms are classified according to their sector of principal activity, disaggregation up to 2-digits of NACE 2008 classification. The present study only considers manufacturing firms.

Table 1 provides a screen-shot of the data broken down by countries and sectors. It can be observed that Italy has the higher number of observations, followed by Spain and France. The number of small-medium enterprises, defined according EU standards as firms with less than 250 employees, covers approximately 95% of the entire sample.

Concerning the two size measures used to define HG and PHG firms (employment and sales) their growth rates distributions display the usual fat tails and tent-like shape already found in previous studies. The parameter b of a Subbotin or Power Exponential distribution estimated via maximum likelihood (see Bottazzi and Secchi, 2006) ranges indeed from 0.48 for Italian firms to 0.60 for Spanish firms in case of employment growth.[5] The distribution of sales growth rates have b very close to 1 in all countries, thus revealing a Laplace distribution. The same results appears stable over the years of the sample period. Also notice that annual sales and employment growth within the sub-sample of HG companies have a relatively high correlation (0.51 Kendall τ, statistically significant).

Table 2 shows the number of HG and PHG firms per sector and coun-

[4] In the empirical literature on firms dynamics the survival bias is often referred to as *attrition bias*. To be precise, we should not say that we compare HG firms with "other firms", but rather HG-and-surviving firms with other-and-surviving. In fact, it could be the case that this specification does, in some case, matter. Due to the nature of our database, however, we are not in the position to test this hypothesis. We omit to further specify this point in what follows.

[5] The Subbotin family of densities possesses the following functional form: $f_s(x) = e^{-\frac{1}{b}|\frac{x-\mu}{a}|^b}/(2ab^{1/b}\Gamma(1/b+1))$, where $\Gamma(x)$ is the Gamma function. The distribution has three parameters, the mean μ, the dispersion parameter a and the shape parameter b. When $b = 2$ the distribution is a Gaussian, while it has fat tails for $b < 2$ and in particular it is a Laplace distribution if $b = 1$.

Table 1: Number of firms by country and sector

NACE	Description	Obs IT	Obs ES	Obs FR
10	Manuf. of food products	721 (684)	633 (614)	384 (368)
11	Manuf. of beverages	144 (141)	126 (116)	60 (59)
13	Manuf. of textiles	493 (471)	203 (199)	65 (60)
14	Manuf. of wearing apparel	274 (260)	98 (96)	40 (38)
15	Manuf. of leather and related products	262 (254)	152 (150)	32 (31)
16	Manuf. of wood and of products of wood and cork	173 (166)	234 (233)	177 (173)
17	Manuf. of paper and paper products	242 (227)	97 (91)	58 (53)
18	Printing and reproduction of recorded media	146 (140)	305 (305)	181 (179)
19	Manuf. of coke and refined petroleum products	40 (37)	7 (5)	5 (5)
20	Manuf. of chemicals and chemical products	449 (422)	197 (189)	107 (89)
21	Manuf. of basic pharmaceutical products and preparations	112 (86)	27 (16)	22 (14)
22	Manuf. of rubber and plastic products	548 (526)	260 (256)	190 (176)
23	Manuf. of other non-metallic mineral products	457 (438)	348 (337)	154 (143)
24	Manuf. of basic metals	360 (333)	127 (120)	36 (33)
25	Manuf. of fabricated metal products	1392 (1356)	911 (907)	579 (559)
26	Manuf. of computer, electronic and optical products	264 (247)	54 (48)	102 (89)
27	Manuf. of electrical equipment	396 (372)	100 (95)	72 (58)
28	Manuf. of machinery and equipment n.e.c.	1198 (1146)	308 (302)	190 (179)
29	Manuf. of motor vehicles, trailers and semi-trailers	172 (148)	104 (92)	67 (63)
30	Manuf. of other transport equipment	88 (81)	23 (22)	25 (21)
31	Manuf. of furniture	311 (306)	245 (243)	73 (72)
32	Other manufacturing	189 (186)	113 (111)	84 (81)
33	Repair and installation of machinery and equipment	113 (109)	224 (224)	263 (257)
Total		8544 (8136)	4896 (4771)	2966 (2800)

Note: Number of firms with less than 250 employees in parenthesis.

try, obtained through the criteria adopted to identify growth status over the period 2006-2011. As expected, the number of persistent high-growth companies is always very limited, regardless of the sector. On average these enterprises cover no more than 2% of the total sample. Similar numbers are obtained if we modify the criteria for identification of HG and PHG firms by either taking less restrictive threshold on the definition (15%) or considering 3 over 5 periods for the identification of persistent high-growth units. In both cases the number of PHG firms increases, but it never exceeds the 5% of the total population. On the other hand, being too restrictive, by fixing a threshold of top 5% or considering 5 out of 5 periods, substantially reduces the number of PHG firms, making the statistical analysis unfeasible.

The characteristics of the companies that we consider in the initial period are productivity, profitability and financial condition. We consider two measures of productivity: we compute a standard labour productivity (LP) index as the ratio between value added and number of employees and we obtain a Total Factor Productivity measure (log(TFP)) as the residual of production function estimation performed through the IV-GMM modified Levinsohn-Petrin procedure, proposed in Wooldridge (2009). This procedure uses the cost of material inputs to control for endogeneity of labour inputs together

Table 2: High-growth and persistent high-growth firms by sector

	Italy			Spain			France		
NACE	**Total**	**HG**	**PHG**	**Total**	**HG**	**PHG**	**Total**	**HG**	**PHG**
10	721	188	23	633	180	11	384	74	4
11	144	23	1	126	32	3	60	11	1
13	493	41	3	203	26	1	65	3	0
14	274	65	8	98	11	0	40	7	0
15	262	52	2	152	31	2	32	5	0
16	173	20	1	234	27	0	177	18	1
17	242	34	3	97	13	0	58	8	1
18	146	15	0	305	44	1	181	21	2
19	40	7	0	7	1	1	5	1	0
20	449	85	6	197	43	3	107	26	2
21	112	28	1	27	10	1	22	5	0
22	548	72	1	260	45	3	190	28	3
23	457	41	4	348	27	2	154	21	1
24	360	44	7	127	17	2	36	4	0
25	1392	174	19	911	88	5	579	74	3
26	264	51	8	54	11	1	102	27	3
27	396	70	7	100	14	2	72	16	0
28	1198	202	21	308	38	5	190	24	3
29	172	22	1	104	16	2	67	9	0
30	88	15	5	23	9	0	25	4	0
31	311	28	5	245	16	1	73	4	0
32	189	37	6	113	22	3	84	11	0
33	113	29	5	225	33	4	263	48	6
Total	**8544**	**1343**	**137**	**4896**	**754**	**54**	**2966**	**445**	**30**

with unobserved heterogeneity. The estimates are performed pooling firms within the same 2-digit level sector, taking value added as a measure of firm output and number of employees and fixed tangible assets as measures of labour and capital inputs, respectively. Concerning profitability, in order to obtain a finer representation of both the operational and more structural capacity to generate value, we compute two indexes: the Return on Sales (ROS), defined as operating margins divided by sales, and the Return on Assets (ROA), defined as operating margins over total assets. Finally, to capture different dimensions of the financial status of the firms, we employ two financial indicators: a flow measure of the capacity to meet short term financial obligations, computed as the ratio between interest expenses and total sales (IE/S) in a given year, and a more long-term measure of leverage, computed as the ratio between long-term debt and total assets (LTD/ASS).

In the robustness analysis we use size, measured as sales or employment consistently with our growth definition, and age, computed by year of foundation, as control variables.

Table 3 provides basic descriptive statistics of the main variables, in three reference years. The broad picture reflects well known differences across coun-

Table 3: Descriptive statistics at aggregate level by country

Variable	2004 Mean	2004 Std	2007 Mean	2007 Std	2010 Mean	2010 Std
Italy						
Size (sales)	24390.50	126458.10	31005.54	154129.30	29200.74	122733.70
Size (no. employees)	86.55	258.87	92.89	290.24	91.08	295.26
LP	66.96	54.26	74.62	57.26	71.06	55.92
log(TFP)	1.54	0.98	1.58	0.98	1.47	1.02
ROA	0.0229	0.0530	0.0292	0.0561	0.0184	0.0547
ROS	0.0485	0.0646	0.0568	0.0645	0.0374	0.0733
IE/S	0.0140	0.0209	0.0156	0.0238	0.0109	0.0142
LTD/ASS	0.0647	0.0935	0.0742	0.0975	0.0799	0.0975
Age	22.85	14.81	25.85	14.81	28.85	14.81
Spain						
Size (sales)	18343.87	283713.20	24108.24	410140.40	22373.36	401268.20
Size (no. employees)	67.79	1005.1960	76.67	1436.51	71.98	1379.97
LP	47.62	211.70	49.31	115.89	46.25	106.20
log(TFP)	1.38	0.78	1.44	0.79	1.34	0.86
ROA	0.0398	0.0668	0.0462	0.0644	0.0068	0.0773
ROS	0.0472	0.0875	0.0615	0.1332	0.0149	0.1520
IE/S	0.0149	0.0242	0.0173	0.0206	0.0182	0.0368
LTD/ASS	0.1498	0.1723	0.0668	0.1167	0.1616	0.1852
Age	15.14	30.73	18.14	30.73	21.14	30.73
France						
Size (sales)	22951.99	227529.00	27767.28	279255.60	27903.35	311334.20
Size (no. employees)	112.87	1049.18	119.28	1161.87	122.38	1328.82
LP	53.81	88.22	58.85	53.19	56.92	65.69
log(TFP)	1.31	0.94	1.34	0.95	1.33	0.97
ROA	0.0493	0.0950	0.0585	0.0970	0.0368	0.1073
ROS	0.0446	0.0744	0.0529	0.0722	0.0318	0.0840
IE/S	0.0079	0.0106	0.0077	0.0099	0.0061	0.0091
LTD/ASS	0.0134	0.0636	0.0552	0.0838	0.0605	0.1009
Age	22.53	19.49	25.53	19.49	28.53	19.49

Note: Sales and LP in thousands of Euros.

tries. Average firm size in terms of sales is similar across Italy and France, while Spanish firms are smaller on average. France firms are however bigger on average in terms of employment, again with the average Spanish firms being smaller than the average Italian companies in the sample. This may also be part of the explanation of the comparatively higher average labour productivity observed for Italian firms. TFP provides similar rankings across countries. Concerning profitability, the average ROA is also higher in France, in all years, while the average ROS is more similar across the 3 countries. Productivity and profitability measures also reveal the fingerprints of the current financial crisis in a sharp decrease in the last reported year, common to all countries. The financial ratios display a ranking in financial fragility across firms in the three countries, with French firms being on average more solid along both the proxies, followed by Italian firms and with Spanish firms coming last as the most vulnerable, especially in the last year, again possibly connecting with the current crisis. Finally notice the differences in age, with Spanish firms on average younger, reflect the typical size structure of the economy. Obviously, the average age of firms is relatively high in all countries (above 15 years old), likely due to the choice to only look at incumbent

Table 4: Distributional comparisons - HG vs. "other" firms

	Country	#Other firms	#HG	ROA	ROS	IE/S	LTD/ASS	LP	log(TFP)
t-test	IT	7201	1343	3.2270**	0.6068	1.4133	-2.3854	4.6209**	3.6505**
	ES	4142	754	-0.2017	-0.4311	1.8697	2.9385*	4.3744**	6.1024**
	FR	2521	445	0.4700	0.1601	1.5756	0.1983	3.3499**	2.3542
WMW test	IT	7201	1343	5970206**	5744248	5894263	5503846*	6196830**	6120352**
	ES	4142	754	1830513	1866924	1936794	1978234**	2032776**	2069670**
	FR	2521	445	689977	682622	658690	669903	720445**	691127*
FP test	IT	7201	1343	2.7732*	0.0663	1.8691	-2.9420*	5.2395**	4.7316**
	ES	4142	754	-0.4381	0.5667	2.4533	3.6261**	4.9935**	5.2137**
	FR	2521	445	1.7153	1.3144	-0.0859	0.9737	3.4720**	2.6773**

Notes: t-test for equality of mean, Wilcoxon-Mann-Witney (WMW) test for equality of medians, and Fligner-Policello (FP) test of stochastic equality.
HG firms as benchmark: positive and significant t statistic indicates HG firms have higher mean; significant WMW statistic indicates HG firms have higher median; positive and significant FP statistic means HG dominates.
Asterisks denote significance levels: * $p < 0.01$, ** $p < 0.001$.

firms along the considered time window.

5 Main results

We start presenting the results of the tests comparing the empirical distributions of the 2004-2005 average values of productivity, profitability and financial indicators. These provide pairwise comparisons across HG, PHG and "other" firms. The null hypothesis of the t test is that the two compared groups have equal mean. We take the HG firms as the benchmark, so that a positive (negative) t-statistic means that HG have a larger (smaller) mean as compared to either "other firms" or PHG firms. The null of the WMW test is equality of medians, while the alternative is designed so that rejection of the null supports that HG firms have a larger median than the other two compared groups. The null of the FP test draws on the concept of stochastic equality and in case of rejection the sign of the FP statistic indicates which group is stochastically dominating the other. We take again the HG firms as the benchmark, so that a positive (negative) FP statistic implies that HG firms have a higher probability to display larger (smaller) initial period values of a given productivity, profitability or financial status indicator, as compared to "other firms" or PHG firms.

In Table 4 we compare HG firms versus "other firms", within each country. Asterisks denote rejection of the null, at different significance levels. The findings are consistent across different statistical tests. First, there is a lacking association between profitability and high-growth performance. When using the ROS equality of distributions cannot be rejected in all countries,

Table 5: Distributional comparisons - PHG vs. HG firms

	Country	#HG	#PHG	ROA	ROS	IE/S	LTD/ASS	LP	log(TFP)
t-test	IT	1206	137	1.4077	0.9513	-1.2922	1.5595	0.2983	0.0316
	ES	700	54	0.5450	0.9077	-1.0010	-1.7201	0.9887	1.6553
	FR	415	30	-0.6960	0.1894	1.8520	-0.9532	-0.7007	-0.6577
WMW test	IT	1206	137	76092	68734	91406	91264	99895	93717
	ES	700	54	21630	20494	18481	19130	20237	17781
	FR	415	30	6004	5382	5334	6444	6355	7131
FP test	IT	1206	137	0.7620	0.5810	-0.7902	0.6140	1.9220	-0.5867
	ES	700	54	1.2410	0.4242	-1.3650	-0.9040	1.6636	2.0393
	FR	415	30	-0.4980	0.4110	-0.1101	-0.2650	-0.5844	-0.3040

Notes: t-test for equality of mean, Wilcoxon-Mann-Witney (WMW) test for equality of medians, and Fligner-Policello (FP) test of stochastic equality.
HG firms as benchmark: positive and significant t statistic indicates HG firms have higher mean; significant WMW statistic indicates HG firms have higher median; positive and significant FP statistic means HG dominates.
Asterisks denote significance levels: * $p < 0.01$, ** $p < 0.001$.

and the ROA distributions do not display statistically significant differences in France and Spain. The only case where we observe some discriminatory power is when we look at the ROA distribution across Italian firms. The sign of both the t and FP statistic is positive, meaning that in this case HG firms have a larger average ROA and their ROA distribution dominates the ROA distribution of the "other firms".[6] Second, we obtain mixed results about the relevance of financial conditions. The estimates on the IE/S ratio reveal no statistically significant differences across groups, while the leverage indicator has a strong discriminatory power, with HG firms less indebted than other firms in Italy, but more indebted in Spain. Finally, we find that HG firms differ from other firms in terms of both labour productivity and the TFP distributions, at a strong significance level. In particular, from the sign of the t and FP statistics we can conclude that HG companies have higher initial efficiency levels, on average, and their LP or TFP distribution dominates the "other firms" distributions, in all the countries considered. Overall, the results suggest that, among the set of growth determinants predicted by the theory, productivity performance stands out as the core channel for high growth. Contrary to expectations, conversely, financial and profitability indicators display a weak or lacking relationship with high-growth status.

The more striking findings emerge however when we compare PHG firms and HG firms. The results, reported in Table 5, contradict the expectation that PHG firms display any peculiarity. The basic insight is indeed that,

[6]This result replicates previous evidence of a lack of correlation between growth and ROS among Italian and French manufacturing firms (Bottazzi et al., 2008, 2010), although those studies do not focus on HG firms.

no matter the economic or financial aspect considered, we are not able to detect any significant difference between the two groups of firms. Firms who display a subsequent pattern of persistent high-growth performance are neither more productive, nor more profitable, nor characterized by a sounder financial situation in the initial years. The finding is robust across the three countries, and irrespective of the statistical test adopted.

Regression results

We next present results of the Multinomial Probit analysis of the impact that initial firm characteristics have on the probability to fall into the HG, PHG or "other" firm growth status.

Table 6 presents the estimates of a full model where the vector of explanatory variables includes all the dimensions of firm characteristics and performance. As before, the latter are all measured as the average across 2004-2005. In all specifications we test robustness of results with respect to the productivity proxy, alternatively including either labour productivity or TFP in the estimation. Since we are primarily interested in the statistical significance, we report estimated coefficients together with robust standard errors computed via bootstrap.[7] Variables are taken in z-scores with zero mean and unitary variance. The marginal effects, computed as standard at the sample mean of the covariates, are thus proportional to the reported coefficients. This allows to compare coefficients magnitudes across variables and, since the sample size does not vary, also across specifications. We select the HG firms as the baseline category, so that a positive (negative) estimated coefficient capture if the corresponding regressor increases (decreases) the odds of belonging to the "other firms" or the PHG firms groups rather than belonging to the HG group.

Results about "other firms" are presented in the left panel, while estimates for PHG firms are reported in the right panel. In Columns 1-6 of both panels we show separate estimates by country. The results for the "other firms" group reveal that efficiency stands out as the main driver of high-growth performance. Indeed, the estimated coefficients on labour productivity are strongly significant in all countries and the pattern is replicated with TFP, with the exception of Spanish firm. The negative sign matches the theoretical expectation that HG firms are more productive than "other firms". The result is in agreement with the univariate distributional analysis,

[7]Reported standard errors obtained out of 100 bootstrap runs, which were enough to obtain convergence. Notice that the same patterns of significance are obtained applying usual sandwich-White type robust standard errors. The same applies to all the results presented in the following tables.

Table 6: Multinomial probit - Main estimates

	Group: *Other firms*								Group: *Persistent HG*							
	Italy		Spain		France		Pooled		Italy		Spain		France		Pooled	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ROS	0.1681	0.2000	0.0737	0.0373	0.0995	0.0313	0.0972	0.0566	0.0436	0.0452	-0.0428	-0.1055	-0.0615	-0.0718	-0.0244	-0.0616
	(0.1130)	(0.1459)	(0.0379)	(0.0396)	(0.0648)	(0.0640)	(0.0622)	(0.0368)	(0.114)	(0.0981)	(0.0777)	(0.0813)	(0.154)	(0.1355)	(0.0537)	(0.0493)
ROA	-0.1901**	-0.2656**	0.0026	-0.0505	-0.0394	-0.0105	-0.0669	-0.0662	-0.0925	-0.1300	0.0776	0.0473	0.103	0.1997	0.0125	0.0533
	(0.0620)	(0.0611)	(0.0525)	(0.0478)	(0.0500)	(0.0523)	(0.0275)	(0.0319)	(0.122)	(0.1167)	(0.0986)	(0.1087)	(0.116)	(0.0899)	(0.0550)	(0.0531)
IE/S	-0.0496	-0.0485	-0.0276	-0.0239	-0.1149	-0.0110	-0.0364	-0.0314	0.0165	0.0189	-0.0085	-0.0118	-0.2328	0.0748	0.0043	0.0134
	(0.0646)	(0.0564)	(0.0513)	(0.0406)	(0.0768)	(0.1011)	(0.0324)	(0.0284)	(0.0403)	(0.0539)	(0.0582)	(0.0666)	(0.200)	(0.1884)	(0.0222)	(0.0303)
LTD/ASS	0.0768	0.0888	-0.0696	-0.0900	-0.0047	-0.0665	-0.0363	-0.0148	-0.1190	-0.0978	0.0701	-0.0451	0.2099	0.2373	-0.0056	-0.0356
	(0.0421)	(0.0353)	(0.0273)	(0.0971)	(0.0975)	(0.0868)	(0.0199)	(0.0201)	(0.0800)	(0.0782)	(0.0525)	(0.0628)	(0.215)	(0.1447)	(0.0462)	(0.0383)
log(LP)	-0.1192**	–	-0.1737**	–	-0.2041**	–	-0.1441**	–	-0.0900	–	-0.1228	–	-0.1920	–	-0.0771	
	(0.0338)		(0.0297)		(0.0491)		(0.0191)		(0.0733)		(0.0759)		(0.131)		(0.0398)	
log(TFP)	–	-0.0841*	–	-0.2730**	–	-0.1085	–	-0.1000**	–	-0.0051	–	-0.1635	–	-0.0389	–	-0.0739
		(0.0277)		(0.0490)		(0.0483)		(0.0175)		(0.0541)		(0.0898)		(0.0982)		(0.0382)
χ^2	42.949**	48.758**	58.492**	54.984**	27.657*	23.246*	70.813**	54.042**	42.949**	48.758**	58.492**	54.984**	27.657*	23.246*	70.813**	54.042**
Pseudo log-likelihood	-4,137.57	-4,117.56	-2,264.89	-2,279.60	-1,362.41	-1,346.84	-7,791.23	-7,791.22	-4,137.57	-4,117.56	-2,264.89	-2,279.60	-1,362.41	-1,346.84	-7,791.23	-7,791.22
Observations	8,544	8,544	4,896	4,896	2,966	2,966	16,406	16,406	8,544	8,544	4,896	4,896	2,966	2,966	16,406	16,406

Notes: Coefficient estimates of Multinomial Probit regression from different specifications of model (4), taking High-Growth firms as the baseline group.
Explanatory variables in z-scores.
Bootstrapped standard errors (100 runs) in parenthesis below the coefficients. Asterisks denote significance levels: * $p < 0.01$, ** $p < 0.001$.

confirming the relevance of productivity performance even when we allow all firm characteristics to simultaneously interact in predicting the growth status. We also observe that profitability, as measured in terms of ROA, plays a role across Italian firms, again in line with the results from the univariate distributional analysis. All the other factors, i.e. the ROS and the financial indicators, on the contrary, are never statistically significant.

The picture changes when we look at the estimates obtained for the probability to fall into the PHG category (columns 1-6 in right panel). In this case none of the explanatory firm attributes displays a statistically significant coefficient. The result confirm the conclusion from the univariate distributional analysis that PHG firms do not differ from HG firms along any of the considered dimensions. Notice that this absence of statistical correlation also downplays the obvious concern with endogeneity and omitted variable bias.

In columns 7-8 of the two panels we replicate the analysis pooling all the observations across the three countries. This allow to check that results do not depend from the relatively low number of observations available in the country by country estimates, especially in the case of PHG firms. Indeed, we confirm that productivity is the strongest driver distinguishing HG firms from "other firms", and the general lack of statistically significant association between persistent high-growth and all the considered firm characteristics.

Overall, our general conclusion is that the main drivers of growth predicted by the theory, and productivity in particular, play some role in shaping high-growth patterns, while they do not seem to be able to distinguish persistent from sporadic high-growth firms.

6 Robustness and extended analysis

We extend the analysis to control for other potentially relevant factors which we have not included in the main estimates. Lacking a specific theoretical guidance, especially concerning the factors driving persistence, we draw from the set of determinants usually investigated in the empirical literature on high-growth firms. First, we want to explore variation of results with respect to sectoral specificities, and especially across sectors characterized by different innovation patterns. This exercise indeed allows us to at least partially consider the role of innovation and technological factors, for which we do not have firm-level proxies in the data. Second, we are able to include two standard demographic characteristics such as size and age. Finally, although the invariance of the main findings across countries already tells that institutional and other country-specific differences can only play a second order role, we still keep our approach to separate the analysis by

Table 7: Multinomial probit - Low vs. High Tech sectors

	Group: *Other firms*						Group: *Persistent HG*					
	Italy		Spain		France		Italy		Spain		France	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
ROS	0.1681	0.2030	0.0745	0.0406	0.1011	0.0345	0.0450	0.0460	-0.0371	-0.1065	-0.0545	-0.0696
	(0.1492)	(0.1462)	(0.0402)	(0.0382)	(0.0679)	(0.0778)	(0.1040)	(0.1033)	(0.0850)	(0.0716)	(0.1390)	(0.1410)
ROA	-0.1901**	-0.2657**	0.00132	-0.0377	-0.0377	-0.0123	-0.0947	-0.1294	0.0720	0.0421	0.1085	0.1980
	(0.0553)	(0.0552)	(0.0495)	(0.0530)	(0.0524)	(0.0548)	(0.1190)	(0.1006)	(0.0985)	(0.0972)	(0.1100)	(0.0953)
IE/S	-0.0496	-0.0480	-0.0269	-0.0260	-0.1127	-0.0202	0.0163	0.0193	-0.00639	-0.0097	-0.2186	0.0805
	(0.0625)	(0.0569)	(0.0667)	(0.0501)	(0.0822)	(0.0947)	(0.0608)	(0.0487)	(0.0574)	(0.0950)	(0.2250)	(0.2229)
LTD/ASS	0.0767	0.0818	-0.0671	-0.0986	-0.00386	-0.0739	-0.1219	-0.0993	0.0787	-0.0424	0.2130	0.2372
	(0.0374)	(0.0375)	(0.0286)	(0.0953)	(0.1040)	(0.0967)	(0.0809)	(0.0857)	(0.0494)	(0.0619)	(0.2600)	(0.1569)
log(LP)	-0.1192**	–	-0.1786**	–	-0.2097*	–	-0.0873	–	-0.1456	–	-0.2180	–
	(0.0321)		(0.0322)		(0.0644)		(0.0765)		(0.0799)		(0.1330)	
log(TFP)	–	-0.0817*	–	-0.3185**	–	-0.1511*	–	-0.0045	–	-0.1378	-	-0.0386
		(0.0256)		(0.0534)		(0.0555)		(0.0517)		(0.0918)		(0.1182)
low_Tech	0.0009	0.1452	-0.1057	0.3117**	-0.0710	0.3691*	0.0561	0.0255	-0.3655	-0.1246	-0.2759	0.0034
	(0.0528)	(0.0593)	(0.0738)	(0.0866)	(0.1180)	(0.1124)	(0.1050)	(0.1002)	(0.2030)	(0.1804)	(0.2320)	(0.2382)
χ^2	45.581**	75.231**	46.647**	64.496**	23.849*	33.622**	45.581**	75.231**	46.647**	64.496**	23.849*	33.622**
Pseudo log-likelihood	-4,137.41	-4,113.20	-2,262.70	-2,271.65	-1,361.52	-1,339.59	-4,137.41	-4,113.20	-2,262.70	-2,271.65	-1,361.52	-1,339.59
Observations	8544	8544	4896	4896	2966	2966	8544	8544	4896	4896	2966	2966

Notes: Coefficient estimates of Multinomial Probit regression from different specifications of model (4), taking High-Growth firms as the baseline group.
Main explanatory variables in z-scores. *low_tech* is a dummy indicating firms belonging to a Low-Tech sector.
Bootstrapped standard errors (100 runs) in parenthesis below the coefficients. Asterisks denote significance levels: * $p < 0.01$, ** $p < 0.001$.

country, allowing for identification of cross-country differences in both the main and the control variables.

Sectoral patterns

In order to explore the role of sectoral specificities, we re-estimate the baseline Multinomial Probit augmented with dummy indicators distinguishing groups of sectors by their innovative characteristics.[8]

In Table 7 we include a simple distinction between Low-tech vs. High-Tech industries, following the standard OECD classification. The dummy *low_tech*, specifically, takes value 1 if a firm is active in a Low-Tech sector. The estimates confirm the main analysis: efficiency (either measured as LP or TFP) emerges as the key characteristic distinguishing HG from "other firms" (with ROA playing a role in Italy), while PHG firms do not differ from HG firms along any of the included dimensions. We also observe that the distinction between Low and High-Tech sectors contributes to explain high-

[8]Notice also that adding a full set of 2-digit dummies creates a too many parameters problem related to the well-known heavy computational burden of Multinomial Probit estimation. Moreover, especially in country-by-country estimates, we do not have enough data points (in the HG and PHG group) to cover the full range of 2-digit sectors.

Table 8: Multinomial probit - Pavitt sectors

	Group: *Other firms*						Group: *Persistent HG*					
	Italy		Spain		France		Italy		Spain		France	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
ROS	0.1686	0.1983	0.0751	0.0432	0.1034	0.0320	0.0456	0.0506	-0.0296	-0.0937	-0.0425	-0.0643
	(0.1476)	(0.1485)	(0.0437)	(0.0408)	(0.0687)	(0.0664)	(0.0907)	(0.1023)	(0.0857)	(0.0812)	(0.1373)	(0.1603)
ROA	-0.1899*	-0.2659**	-0.0009	-0.0175	-0.0372	-0.0153	-0.0972	-0.1316	0.0631	0.0373	0.1047	0.2131
	(0.0622)	(0.0566)	(0.0547)	(0.0548)	(0.0478)	(0.0445)	(0.1043)	(0.1143)	(0.1088)	(0.1203)	(0.1002)	(0.1093)
IE/S	-0.0493	-0.0496	-0.0276	-0.0234	-0.1167	-0.0022	0.0159	0.0201	-0.0094	-0.0092	-0.2621	0.1183
	(0.0564)	(0.0649)	(0.0560)	(0.0461)	(0.0773)	(0.0912)	(0.0401)	(0.0591)	(0.0445)	(0.0531)	(0.1938)	(0.1659)
LTD/ASS	0.0767	0.0887	-0.0681	-0.0972	-0.0055	-0.0698	-0.1206	-0.0977	0.0735	-0.0429	0.2035	0.2653
	(0.0388)	(0.0450)	(0.0648)	(0.0937)	(0.0982)	(0.1085)	(0.0754)	(0.0790)	(0.0543)	(0.0562)	(0.2460)	(0.1457)
log(LP)	-0.1214**	–	-0.1814**	–	-0.2191*	–	-0.0862	–	-0.1486	–	-0.2296	–
	(0.0314)		(0.0346)		(0.0677)		(0.0659)		(0.0852)		(0.1054)	
log(TFP)	–	-0.0582	–	-0.3738**	–	-0.0919	–	-0.0137	–	-0.1617	–	-0.1100
		(0.0276)		(0.0495)		(0.0541)		(0.0497)		(0.0917)		(0.0804)
Pavitt_SB	0.0637	-0.1786	0.3070	-0.8426*	-0.0337	-0.5262*	0.3307	0.0089	0.5546	-0.1692	-0.0432	-0.1892
	(0.1248)	(0.1242)	(0.2930)	(0.2868)	(0.2114)	(0.1938)	(0.2490)	(0.2231)	(1.7930)	(1.4329)	(2.3799)	(2.5043)
Pavitt_SS	-0.0119	-0.0996	-0.0063	0.3941*	-0.1426	-0.0485	-0.1862	0.0092	-0.1914	0.3801	-0.6248	0.3931
	(0.1088)	(0.1009)	(0.1308)	(0.1331)	(0.1417)	(0.1478)	(0.2617)	(0.1967)	(0.3137)	(0.2791)	(0.2551)	(0.3138)
Pavitt_SD	-0.0100	0.1953**	-0.0804	0.4887**	-0.1514	0.2542*	0.0561	-0.0755	-0.3172	-0.0506	-0.3238	-0.0286
	(0.0516)	(0.0541)	(0.0563)	(0.0655)	(0.0906)	(0.0910)	(0.0994)	(0.0957)	(0.1428)	(0.1709)	(0.1861)	(0.2489)
χ^2	67.072**	87.584**	61.534**	135.815**	31.264*	53.480**	67.072**	87.584**	61.534**	135.815**	31.264*	53.480**
log pseudolikelihood	-4,135.76	-4,102.53	-2,260.97	-2,239.08	-1,359.26	-1,333.00	-4,135.76	-4,102.53	-2,260.97	-2,239.08	-1,359.26	-1,333.00
Observations	8544	8544	4896	4896	2966	2966	8544	8544	4896	4896	2966	2966

Notes: Coefficient estimates of Multinomial Probit regression from different specifications of model (4), taking High-Growth firms as the baseline group.
Main explanatory variables in z-scores. *Pavitt_SB*, *Pavitt_SS* and *Pavitt_SD* are dummy variables indicating if a firm belongs to Science Based (SB), Specialised Supplier (SS) or Supplier Dominated (SD) sectors according to Pavitt taxonomy.
Bootstrapped standard errors (100 runs) in parenthesis below the coefficients. Asterisks denote significance levels: * $p < 0.01$, ** $p < 0.001$.

growth, with firms in Low-Tech sectors having a higher probability to fall into the "other firms" category than to fall into the HG group. Notice that the Low-Tech dummy tends to become significant (in Spain and France) in the specifications with TFP, while it is not significant if we use LP to proxy for efficiency. Our explanation is that LP absorbs part of the explanatory power related to capital intensity, which we can instead control for through the TFP measure. This suggests a positive correlation between innovativeness and capital intensity, which we indeed verify to be present in the data, with firms active in High-Tech sectors having higher LP, on average, no matter their growth-status. Nevertheless, being active in High-Tech sectors does not affect the probability to sustain high-growth performance over time: the Low-Tech dummy coefficient is not statistically different from zero in the PHG equation.

Table 8 presents a similar exercise where we explore variation across sectors belonging to the classes identified by the classical Pavitt (1984) taxonomy of sectoral sources of innovation. The included dummy variables correspond to Science Based (SB), Specialized Suppliers (SS) and Supplier

Dominated (SD) sectors, while Scale Intensive sectors are in the left-out baseline category.

Also in this case the estimated coefficients are broadly consistent with the picture from the main estimates. We indeed still find the two productivity proxies as the main driver of HG performance, and fully confirm the inability of firm attributes to predict persistent high-growth. Concerning the role of sectoral patterns, results are similar to the above Low-Tech vs. High-Tech analysis. First, sectoral specificities contribute to explain the HG status, and we again observe that sectoral dummies tend to be statistically significant (in Spain and France) only when entered jointly with TFP, in line with the above discussion about capital intensity across differently innovative sectors. The estimated coefficients, when significant, have the expected sign: ceteris paribus, being active in "more innovative" science based (SB) sectors increases the probability (negative coefficient) to be in the baseline category of HG firms, while being active in "less dynamic" supplier dominated (SD) sectors associates with a reduced probability (positive coefficient) to be in the HG group. Second, and perhaps more interesting, sectoral differences do not provide any statistically significant contribution to explain persistence of high growth status.

Size and Age

We further augment the baseline specification including age and size (number of employees). Previous evidence on the demography of HG firms suggests that these firms tend to be young and small. We test here if, in addition, age and size are also distinguishing features of PHG firms.

Results are presented in Table 9. Concerning the main explanatory variables, we broadly confirm the conclusion that productivity is the strongest predictor of the probability to experience high growth, although size and age do absorb part of the explanatory power of TFP. Also, we once again obtain that none of the main regressors displays any association with the probability to achieve persistent high growth. On the contrary, age and size do play a role. Confirming previous findings in the literature, they both increase the probability to be in the HG group as compared to the probability to fall into the "other firms" category, with strong statistical significance. Moreover, PHG firms seem also to be smaller than HG firms, at least in the Italian sample.

Motivated by these findings, we look deeper into the interaction of each main firm characteristic with both size and age. We split the country samples into age and size classes according to firms' age and size in the first year of the sample, and then repeat an FP test to compare the empirical distribution

Table 9: Multinomial probit - Age and Size

	Group: *Other firms*						Group: *Persistent HG*					
	Italy		Spain		France		Italy		Spain		France	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
ROS	0.1720	0.1985	0.0690	0.0195	0.0629	-0.0058	0.0362	0.0258	-0.0331	-0.0911	-0.0729	-0.0612
	(0.1457)	(0.1449)	(0.0385)	(0.0393)	(0.0700)	(0.0727)	(0.100)	(0.1034)	(0.0838)	(0.0932)	(0.1600)	(0.1475)
ROA	-0.212**	-0.2867**	0.0332	-0.0449	0.0182	0.0294	-0.0458	-0.0971	0.0536	0.0207	0.0837	0.1701
	(0.0596)	(0.0580)	(0.0486)	(0.0454)	(0.0473)	(0.0632)	(0.1170)	(0.1192)	(0.1050)	(0.0981)	(0.1070)	(0.1004)
IE/S	-0.0287	-0.0262	-0.0169	-0.0194	-0.0711	0.0312	0.0204	0.0253	-0.0110	-0.0200	-0.3127	0.0537
	(0.0404)	(0.0355)	(0.0575)	(0.0425)	(0.0832)	(0.0925)	(0.0471)	(0.0441)	(0.0692)	(0.1088)	(0.1950)	(0.2632)
LTD/ASS	-0.0217	-0.0073	-0.0135	-0.0498	-0.00793	-0.0577	0.00152	-0.0009	0.0539	-0.0736	0.1744	0.2201
	(0.0421)	(0.0338)	(0.0298)	(0.0288)	(0.0906)	(0.0920)	(0.0694)	(0.0758)	(0.0534)	(0.0660)	(0.1990)	(0.1679)
log(LP)	-0.1040*		-0.2571**		-0.227**		-0.1480		-0.1276		-0.1673	
	(0.0332)		(0.0334)		(0.0542)		(0.0662)		(0.0792)		(0.1090)	
log(TFP)		-0.0314		-0.2556**		-0.0319		-0.0531		-0.1916		-0.0719
		(0.0300)		(0.0552)		(0.0529)		(0.0617)		(0.0921)		(0.1111)
AGE	0.3551**	0.2965**	0.6093**	0.3938**	0.284**	0.2241*	-0.2243	-0.1584	-0.1628	-0.4216	-0.4253	-0.2077
	(0.0422)	(0.0427)	(0.1000)	(0.0884)	(0.0740)	(0.0702)	(0.1290)	(0.1050)	(0.3690)	(0.3675)	(0.2740)	(0.3353)
log(SIZE)	0.4309**	0.4243**	0.1933**	0.1299*	0.217**	0.1988**	-0.4038**	-0.3169**	-0.1975	-0.2678	-0.0107	-0.0819
	(0.0359)	(0.0358)	(0.0431)	(0.0412)	(0.0477)	(0.0459)	(0.0596)	(0.0774)	(0.1070)	(0.1131)	(0.1170)	(0.1423)
χ^2	440.814**	514.126**	191.485**	100.687**	90.145**	68.045**	440.814**	514.126**	191.485**	100.687**	90.145**	68.045**
log pseudolikelihood	-3,866.24	-3,885.17	-2,181.29	-2,229.30	-1,316.03	-1,314.82	-3,866.24	-3,885.17	-2,181.29	-2,229.30	-1,316.03	-1,314.82
Observations	8544	8544	4896	4896	2966	2966	8544	8544	4896	4896	2966	2966

Notes: Coefficient estimates of Multinomial Probit regression from different specifications of model (4), taking High-Growth firms as the baseline group.
Explanatory variables in z-scores. SIZE measured as number of employees.
Bootstrapped standard errors (100 runs) in parenthesis below the coefficients. Asterisks denote significance levels: * $p < 0.01$, ** $p < 0.001$.

of productivity, profitability and financial indicators across HG and PHG firms within each size and age class. Employment classes mimic standard EUROSTAT distinction, and we compare Micro-Small firms (< 50 employees) against Medium-Large sized firms (≥ 50 employees), putting Medium and Large firms together to have a reasonable number of observations in this class. The definition of age classes is more an attempt of ours to have at least some PHG firms in all categories: we distinguish between Young (≤ 5 years old), Medium-aged (in between 6 and 20 years old) and Old firms (≥ 20 years old).

With some caveats due to the low number of observations, the results in Table 10 show that the null of distributional equality between PHG and HG firms cannot be rejected, for all indicators and no matter the age or size class considered. Once again corroborating our main conclusions, superior economic or financial performances do not actually stand out as distinguishing features of persistently high growing firms.

Table 10: FP test by Age and Size - PHG vs. HG firms

Country	# HG firms	# PHG firms	ROA	ROS	IE/S	LTD/ASS	LP	log(TFP)
Age classes								
Young								
IT	219	39	-0.9140	0.3622	1.3420	0.8080	0.6261	-1.0140
ES	180	25	0.9511	0.1178	-1.4500	-0.2851	0.2490	0.8822
FR	90	10	-0.0422	1.7588	0.9970	-0.3272	0.5636	-0.9444
Medium								
IT	531	64	1.7733	0.6670	-1.2200	0.4161	0.9200	-0.6505
ES	426	25	0.7131	0.5799	-0.9333	-1.2450	2.2390	1.3570
FR	212	16	0.0540	0.1866	-0.6373	0.0166	1.7410	0.3120
Old								
IT	456	34	0.2088	0.0888	-0.5722	-0.7651	1.2758	0.9080
ES	94	4	0.6470	0.1355	0.9359	0.7011	-0.1000	-1.0020
FR	113	4	-0.8199	-0.3400	-0.0070	-0.2479	-0.3757	-0.1611
Size classes								
Small								
IT	882	120	1.0490	0.9122	-1.1400	-0.1099	-0.0550	-0.2466
ES	622	53	1.1111	0.2340	-1.4111	-0.9800	1.4371	1.9580
FR	339	26	-0.2777	0.5370	-0.1291	-0.2877	1.5262	-0.1955
Medium/Large								
IT	324	17	-1.5788	-1.3180	1.9870	0.7233	-0.5566	0.0778
ES	78	1	-	-	-	-	-	-
FR	76	4	-0.8333	-0.5680	-0.2411	-0.0440	-0.7799	0.0400

Notes: Fligner-Policello (FP) test of stochastic equality.
HG firms as benchmark: positive and significant FP statistic means HG dominates.
Asterisks denote significance levels: * $p < 0.01$, ** $p < 0.001$.

7 Conclusion

Persistent high growth performance is a topic of great interest for its potential implications for both academic scholars and policy makers, but we are still missing a deep understanding of this phenomenon. From models of firm-industry dynamics we might expect firms characterized by higher efficiency, higher profitability and sounder financial conditions to be comparatively more able to achieve high growth, but the literature does not provide a theoretical framework explicitly targeting persistent high growth as an emergent property. In this paper, exploiting cross-country data on Italian, French and Spanish manufacturing firms, we have addressed empirically the question whether there is a relationship between that set of key firm characteristics and persistent high growth. To the best of our knowledge, this is the first study posing this question. Previous studies have indeed so far revealed that outstanding persistent growth performers appear as rare exceptions, but we lack of attempts to investigate the determinants of persistent high growth.

Our findings provide a negative result. We do find some support that efficiency of the firm (proxied by labour productivity and TFP) is strongly associated with the process of high-growth. However, neither productivity nor the other supposedly key drivers of growth stand out as significant predictors of persistently high growth performance. The result is robust across countries, it does not change in relationship to sectoral specificities in innovativeness, and it holds irrespective of age and size of the firms, although persistently high growers display a weak tendency to differ in terms of these latter demographic characteristics, being relatively younger and smaller.

Of course, there is a number of other potential factors that may sustain high growth over time and that we have not directly explored in this study. Among more economic drivers, a natural extension of the analysis would be to provide a more precise and detailed identification of the innovative and technological performance of firms, for which we do not have data. Other determinants maybe of more direct derivation from management research, looking deeper into organizational characteristics, or to the potential role of differences in underlying firm strategies and managerial or entrepreneurial characteristics. Moreover, one cannot rule out, at least in principle, that persistent high-growth primarily occurs at random, guided by "mere luck", and it would thus be interesting to test the explanatory power of null models providing random assignment of growth performance.

The research agenda has just begun and many avenues for further research are open. Yet, within their limitations, our findings represent a challenge for the theory and also raise concerns about the possibility to design new policies in support of persistent high-growth firms, as well as about the longer run effectiveness of existing policies targeting high growth companies.

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