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 framework a valid explanation for persistent high corporate 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 "simply" exhibit high growth. The finding is robust across countries, across sectors displaying different innovation patterns, and also controlling for demographic characteristics such as age and 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). These companies attract 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). Managers and consultants seek to understand and replicate within their own business the 'best-practices' which can guarantee superior performance. Policy-makers are particularly interested in the early identification of high-growth firms because of their extraordinary contribution to new jobs creation, and we indeed observe 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, linking high-growth to both macro-economic or institutional vis a vis more micro, firm-specific factors, especially looking at mere demographic variables such as age and size, or to more structural determinants such as firm innovativeness (see the short review in Section 2).

In this paper we take a different approach. Instead of focusing on the identification of those characteristics which make a firm a high growth firm at a given point in time, we want to see which factors make it a *persistently* high-growing firm. Indeed, whatever the determinants of an observed high growth rates, they have a more relevant economic impact and they result more interesting to practitioners and promising to policy makers, if the performing abilities they induce in the company are to some extent structural or, at least, persistent. As a matter of fact indeed 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, year after year, expansion.

While empirical research has for long concentrated on persistence of firm growth rates, and admittedly with mixed results, the study of persistence of high-growth patterns is only of very recent development. The few existing studies (Coad, 2007; Coad and Hölzl, 2009; Capasso et al., 2013), moreover, limit their attention to mere demographic characteristics, such as size and age. More specifically, we do not know of previous research addressing whether persistent high-growth firms do display any specific difference in terms of more structural characteristics and performance with respect to firms that display "spurs" of high growth, but are not able to consistently sustain high growth rates over longer periods of time.

In performing our analysis, we take as our reference framework the existing theories of firm-industry dynamics with heterogeneous firms. Although none of the models specifically addresses the question of the expected abundance of high-growth firms and their behavior over time, there is a common core of predictions, and often a shared set of hypothesis, which are strictly related to our investigation. First, productivity (as a summary measure of idiosyncratic characteristics like capabilities, organizational or managerial specificities, quality and innovative differences), profitability and financial conditions are the key driving forces of growth. 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. In all these models the competitive advantage, even when temporary, stems from specific elements of the firm's operative activities, and it is consequently viewed as a structural aspect which influences firm performances over a relative long period of time. Indeed due to the presence of market imperfection or institutional frictions, the "good firms", innovative entrants or successful incumbents, enjoy a rapid initial expansion which progressively slows down as the new optimal size is approached. 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 from Penrose (1995) to Teece et al. (1997)). Ultimately, these mechanisms induce the same "reversion to the mean" effect in firms' growth rates. In this respect, we can say that all these theories and models are consistent with the emergence of extremes growth events characterized by a certain degree of persistence, so that high-growth firms and persistent high-growth firms should represent similar, if not identical, subsets of productive units.

The analysis proceeds as follows. Exploiting panel data on Italian, French and Spanish manufacturing incumbents, we identify high-growth companies, and within this group, the persistent outstanding ones. It will emerge 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 performances. We perform both a non-parametric and parametric analysis. First, we explore if a set of key variables, taken as proxies of various aspects of firm 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 show our main results, while robustness checks are reported in Section 6. We conclude in Section 7.

2 Related literature

The present paper contributes to different streams of empirical and theoretical research on firm growth.

First, our study is directly related to the empirical literature concerned with the identification and characterization of high-growth companies. The basic 'styled facts' emerged 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. The influential contribution by Delmar et al. (2003) has however highlighted that high-growth firms do not all grow in the same way, and that results can be sensitive to alternative size-growth proxies as well as to alternative criteria to identify high-growth. Using a sample of Swedish firms 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.

We derive from these studies that there is no a unique best way to measure corporate high growth, motivating us to adopt a multidimensional measurement criterion and to embark into a series of robustness checks with respect to possibly alternative criteria.

Second, this work also relates with empirical studies on the determinants of high-growth performance. On the one hand, some scholars have searched for the role of institutional or broadly speaking macro-level external factors. Among others, Davidsson and Henrekson (2002), using a panel of Swedish firms 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 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. On the other hand, more recently, scholars have looked to more micro-level determinants of high growth, and to innovation-related drivers in particular. 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. The 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.

With respect to these studies, we make two distinct contributions. First, whereas they all raise interesting issues, our reading is that they have developed lacking a clear theoretical guidance. We want therefore step back and refer more closely to what existing theories suggests us to look at in the search for the drivers of high growth. Second, none of these studies makes the further step to also include persistently high-growth performance into the analysis.

By making these contributions, our study relates in turn to two further strands of literature.

We draw our theoretical background from models of firm-industry evolution with heterogeneous firms, originally developed within the disequilibrium-evolutionary approach (see, e.g., Nelson and Winter, 1982; Silverberg et al., 1988; Dosi et al., 1995; Metcalfe, 1998) and more recently knowing a widespread diffusion also within more standard equilibrium frameworks (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, they share a common mechanism of firm selection and growth, which is made explicit in disequilibrium dynamics models, while implicitly described as the in equilibrium models as the convergence to the equilibrium path. The predicted pattern starts typically with an idiosyncratic shock as the first driver, affecting firm-specific unobserved factors such as technological and organizational traits, capabilities, strategic and managerial practices, which 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, allow firms to dispose of the resources needed to invest and pursue further growth, especially in presence of financial market imperfections. 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 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).

In addition, the empirical literature on persistence of firm growth does not help. A huge amount of studies tries 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. 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. 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. 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

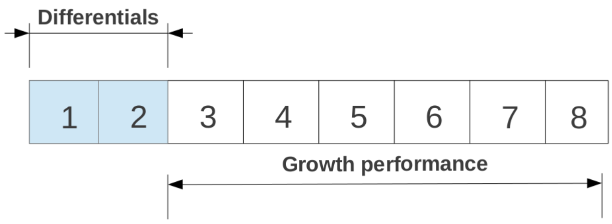

Figure 1: Partitioning criterion: first and second time span

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.

Overall, none of these studies address if more economic or financial factors, beyond and above demographic characteristics such as size and age, 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 growth should occur in favour of the more efficient and more profitable firms, and that sounder financial conditions should help accessing the external resources needed to finance investment 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 ? 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 that we design 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 period I to measure "initial" firm characteristics, which we next seek to map into high-growth, persistently high-growth or "normal" growth performance measured over period II.

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, in how we identify persistent high-growth (PHG) performance. There are no commonly accepted identification criteria in the literature, due to the quite disparate approaches followed in previous studies. First, 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. On the other hand, the 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 sector-wide factors common to all firms in a sector, 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).[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

[1]Further details on the sample are presented in the data Section below. The main conclusions of the article are robust to different partitioning of the sample period. Results are available upon request.

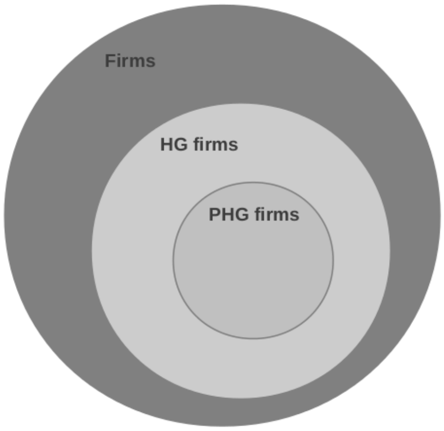

Figure 2: Three sub-samples after the identification and selection step

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, persistently 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 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.

[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 market share and physical output do not benefit of the same property), and they are not too much related to the capital intensity of the industry (as opposed to total assets).

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 with less restrictive definitions (consider 15 or 20 %), 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 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 20 or 15 %) 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

We perform two types of statistical analysis to identify the association between growth performance and initial economic and financial factors.

First, we perform a comparison of the empirical distribution of initial firm characteristics across the three groups of HG, PHG and other firms. For this purpose, we compute the firm-level average of productivity, profitability and financial performance over the two initial years which are not used to identify HG and PHG patterns, and apply the Fligner and Policello (1981) test of distributional equality (hereafter, FP) to pairwise comparisons across growth status. Several alternative methodologies exist to perform such kind of comparisons. The FP procedure however is more general in that it makes less restrictive assumptions. First, the FP test can be applied in comparing uneven samples, as it is likely to be the case with our data, given the quite

[3]Detailed results for the alternative specifications are available upon request.

unequal number of firms falling into the three growth categories. Second, as a non-parametric test, it does not assume normality and equality of variance across the compared samples. Further, while other non-parametric tests for equality of distributions assume that the compared samples only differ for a shift of location, the FP test avoid this hypothesis, which is clearly too strong when dealing with firm-level variables.[4]

Second, 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

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

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]To check the robustness of our findings, we also run a simple t-test and a Wilcoxon-Mann-Witney test. Results were consistent with the findings from the FP procedure.

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. It 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.[5] All 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 growth measures employed to define HG and PHG firms, employment and sales, their growth rates distributions display the usual Laplace shape already found in previous studies. The shape appears stable over the years of the sample period and irrespective of the country considered (results available upon request). 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-

[5] 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 firms that are both “other” *and* surviving. Since this point is understood we omit the further specification in what follows. 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.

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)	4897 (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 with slightly less restrictive thresholds in the definition of HG or PHG firms. As a further check, we have verified that we do identify basically the same firms as HG and PHG firms if we use two separate uni-variate criteria based on sales or employment growth only.

The characteristics of the companies that we consider in the initial period are productivity, profitability and financial condition. We proxy productivity through a standard labour productivity (LP) index calculated as the ratio between value added and number of employees. Data do not permit a reliable computation of multi-factor productivity, as measures of physical capital and intermediate inputs, required for the estimation of the production function, are lacking. Concerning profitability, in order to obtain a finer representation of both the operational and more structural capacity to generate value, we examine 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

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	224	33	4	263	48	6
Total	**8544**	**1343**	**137**	**4895**	**754**	**54**	**2966**	**445**	**30**

the financial status of the firms, we employ two financial indicators: a short term flow measure of the capacity to meet 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).

We also exploit other more demographic characteristics, as control variables in performing some of the robustness analysis. These are: size, taking sales and employment consistently with our growth definition, and age, computed by year of foundation.

Table 3 provides basic descriptive statistics of the main variables, in three reference years. The broad picture reflects well known differences across countries. 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. Concerning profitability, the average ROA is also higher in France, in all years, while the average ROS is

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
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
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
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.

more similar across the 3 countries, and we also observe the fingerprints of the current financial crisis in a common sharp decrease of profitability in the last reported year. The financial ratios reveal 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, reflecting as typical the 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 firms along the considered time window.

5 Main results

We start presenting the results of the Fligner and Policello(1981) test of distributional equality, making pair-wise comparisons of the empirical distribution of the 2004-2005 average values of productivity, profitability and financial variables across HG, PHG and other firms.

Formally, the null hypothesis of the test is the stochastic equality of the compared samples and in case of rejection the method detects which of the two compared distributions statistically dominates the other. This latter information is given by the sign of the FP statistic, depending on which group of firm is taken as the benchmark: a positive sign implies that the benchmark group has a higher probability to take higher initial period values of productivity, profitability or financial status indicator.

Table 4: FP test - HG (benchmark) vs. 'other firms'

Country	**# Other firms**	**# HG firms**	**ROA**	**ROS**	**IE/S**	**LTD/ASS**	**LP**
IT	7187	1357	2.7732**	0.0663	1.8691	-2.9420**	5.2395***
ES	4146	749	-0.4381	0.5667	2.4533*	3.6261**	4.9935***
FR	2526	440	1.7153	1.3144	-0.0859	0.9737	3.4720***

Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

In Table 5 we compare HG (benchmark) versus 'other firms', within each country. The findings at least partially corroborate the theoretical expectations. First, we do find a positive and strongly significant association between productivity and future growth performance: high-growth companies clearly display higher initial efficiency levels, irrespective of the country considered. This factor seems thus fully confirmed as a core channel for high growth. Second, there seems to be a lacking association between profitability and high-growth performance. We cannot reject the null of equality only for Italian firms if we look at the ROA distributions. The sign on the FP statistic is positive, so that the distribution of HG firms dominates the distribution of other firms. Equality of distributions cannot instead be rejected in all countries when using the ROS.[6] Finally, we obtain mixed results also about the relevance of financial conditions. The estimates on the IE/S ratio reveal that HG and other firms display distributional differences only in Spain, but with a relatively low level of statistical confidence (5%). We do not observe any significant difference in the other two countries. Leverage seems instead to have a stronger discriminatory power, with HG firms less indebted than other firms in Italy, but more indebted in Spain.

The more striking findings emerge however when we compare PHG firms (benchmark) and HG firms. The results, reported in Table 5, contradict the expectation that PHG firms display any peculiarity. The basic insight is indeed that, no matter the economic or financial aspect considered, we

[6]This result mimics some previous evidence of a lacking 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.

Table 5: FP test - PHG (benchmark) vs. HG firms

Country	# HG firms	# PHG firms	ROA	ROS	IE/S	LTD/ASS	LP
IT	1228	129	-1.2608	0.0553	1.7368	-0.9752	-1.1153
ES	694	55	-0.8195	-1.0078	0.0012	-0.9637	-2.4182*
FR	402	38	1.7958	1.0551	0.5976	2.0272*	0.4252

Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

are not able to detect any statistically 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.

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 measures of firm characteristics at the same time. As before, these are all measured as the average across 2004-2005. Since we are primarily interested in the statistical significance, we report estimated coefficients together with robust standard errors (marginal effects available upon request). 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 other firms (top panel) or PHG firms (bottom panel) rather than belonging to the HG group.

In Column 1 we show pooled estimates across the three countries. Results on the estimated coefficients for the other firms group (top panel) suggest that both profitability (ROA) and efficiency significantly impact on growth status. The negative signs confirm the theoretical expectation that HG firms are more productive and more profitable. The stronger significance for labour productivity signals that efficiency is indeed more tightly linked with growth status. Financial factors, on the other hand, do not appear do have a role. Compared to the univariate distributional comparisons, therefore, we still get that efficiency and, to same extent, profits matter for high-growth performance, while finance is less relevant once we allow for all variables to simultaneously interact in predicting the growth status.

By looking at the estimates obtained for persistent high-growth firms

Table 6: Multinomial probit - main estimates

Variables	(1) Pooled	(2) Italy	(3) Spain	(4) France
Group: *Other firms*				
ros	1.493	2.581	1.132	1.528
	(1.69)	(1.79)	(1.90)	(1.51)
roa	-1.112*	-3.159***	0.0428	-0.655
	(-2.43)	(-3.47)	(0.05)	(-0.83)
ie/s	-1.770	-2.409	-1.341	-5.584
	(-1.67)	(-1.35)	(-0.94)	(-1.51)
ltd/ass	-0.294	0.623	-0.564	-0.0382
	(-1.95)	(1.07)	(-1.82)	(-0.05)
log(lp)	-0.272***	-0.225***	-0.327***	-0.385***
	(-7.49)	(-3.68)	(-5.28)	(-3.50)
Group: *Persistent HG*				
ros	-0.375	0.669	-0.657	-0.944
	(-0.50)	(0.42)	(-0.67)	(-0.44)
roa	0.208	-1.536	1.290	1.719
	(0.25)	(-0.83)	(0.76)	(0.94)
ie/s	0.208	0.800	-0.412	-11.32
	(0.39)	(1.25)	(-0.51)	(-1.26)
ltd/ass	-0.0453	-0.965	0.569	1.703
	(-0.15)	(-1.56)	(1.47)	(1.59)
log(lp)	-0.145	-0.170	-0.231	-0.362
	(-1.86)	(-1.22)	(-1.50)	(-1.62)
χ^2	74.57***	49.63***	47.91***	23.29**
log pseudolikelihood	-7791.23	-4137.57	-2264.89	-1362.41
Observations	16406	8544	8496	2966

high-growth firms (HG) as baseline group
t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

(bottom panel), the picture changes completely. In line with results from distributional analysis, none of the explanatory firm attributes display statistically significant coefficients. The main drivers of growth predicted by theory, in other words, do not provide any contribution to determine the probability of achieving persistent high growth performance. Notice that this negative result (i.e., absence of statistical correlation) also downplays the obvious concern with endogeneity and omitted variable bias.

Columns 2-4 replicate the same analysis separately by country. Of course the number of observations, especially in the PHG group decreases considerably. Notwithstanding, we confirm the main message from pooled estimates. Regardless the country, indeed, we observe that, first, productivity is the strongest driver distinguishing HG firms from other firms. Second, we again observe a general lack of statistically significant association between persistent high growth and all the considered firm characteristics.

Overall, our general conclusion is that the set of determinants that theory predicts to be key for growth do play some role in shaping high-growth patterns, while they cannot explain persistent high-growth performance.

6 Robustness and extended analysis

We extend the analysis to control for potentially relevant factors which we have not included in the main estimates. Lacking a specific theoretical guidance, especially concerning factors driving persistence, we draw from the set of potential determinants suggested by empirical studies on high-growth firms. First, we are able to include two standard demographic characteristics such as size and age. Second, 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 unfortunately do not have firm-level proxies in the data. Finally, the observed invariance of the main findings across countries already tells that a further potential driver suggested in the literature, that is broadly intended institutional country-specific differences, can only play a second order role. Anyhow, we still keep our approach to separate the analysis by 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.[7]

In Table 7 we include a simple distinction between Low-tech vs. High-Tech industries, following the standard OECD classification. The dummy low_{innov}, specifically, takes value 1 if a firm is active in a Low-Tech sector. The estimates confirm the main analysis: productivity emerges as the only key characteristic distinguishing HG from other firms, while PHG firms do not differ from HG firms along any of the included dimensions. Further, the distinction between Low and High Tech sectors by itself does not contribute to explain HG and PHG performance, a part from a barely significant coefficient on PHG firms in Spain.

Table 8 present a similar exercise, where we instead explore variation across the classes of sectors identified as different according to the standard 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 consistent with the picture from the main estimates. And, again sectoral specificities do not play any statistically significant role.

Size and Age

We further augment the baseline specification including age and size (number of employees). Previous evidence on demography of HG firms suggests that these firms are comparatively younger and smaller than other firms. We test here if, in addition, age and size are also distinguishing features of PHG firms.

Results are presented in Table 9. Concerning our main variables, we broadly confirm the conclusion that productivity is the the strongest predictor of increases in the probability to experience high growth as compared, while none of the main regressors display clear-cut effect on the probability to achieve persistently high growth. On the contrary, age and size do play a role. Confirming expectations, they both increase the probability to be in the HG group as compared to in 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. In this case we also observe some interaction with productivity, which indeed turns barely significant, with a negative sign.

[7] 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.

Motivated buy these findings, we look deeper into the interaction of each main firm characteristic with both size and age. We split the country samples in classes based on age and size (again in terms of employment) measured in the first year of the sample, and then repeat the FP test to compare productivity, profitability and financial indicators distributions across HG and PHG firms within each size and age class. Employment classes mimic standard EUROSTAT distinction between Micro-Small firms (< 50 employees), Medium-sized firm (with employment in between 50 and 250 units) and Large companies (≥ 250 employees). The definition of age classes is more an attempt of ours to have at least some PHG firms in all categories. We define Young (≤ 8 years old), Medium (in between 9 and 25 years old) and Old firms (≥ 25 years old).[8]

With some caveats due to the low number of observations, the results in Table 6 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, superior economic or financial performance does not actually stand out as distinguishing features of persistently high growing firms.

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 results. We do find some support that

[8] In some cases, anyway, and especially for France, the number of PHG firms in some of the age or size classes is zero, or too small to draw credible conclusion. The FP test is known to have some discriminatory power with at least 10-15 observations in the smaller of the two compared distributions.

efficiency of the firm (proxied by labour productivity) 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 persistent high-growth 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 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 managerial research, looking deeper into organizational characteristics, and to the potential role of differences in underlying firm strategies. Moreover, one cannot rule out, at least in principle, that persistent high growth primarily occur at random, guided by 'mere luck'.

The research agenda has just begun and many avenues for further research are open. Yet, within its limitations, our analysis represents a challenge for the theory and also raises caution about how we can design new policies supporting persistent high growth, and about the longer run effectiveness of existing policies targeting high growth companies.

Table 7: Multinomial probit - Low vs High Tech sectors

Variables	(1) Italy	(2) Spain	(3) France
Group: *Other firms*			
ros	2.581	1.144	1.544
	(1.79)	(1.93)	(1.52)
roa	-3.158***	0.0219	-0.627
	(-3.47)	(0.03)	(-0.80)
ie/s	-2.409	-1.308	-5.478
	(-1.35)	(-0.92)	(-1.48)
ltd/ass	0.622	-0.545	-0.0313
	(1.06)	(-1.72)	(-0.04)
log(lp)	-0.225***	-0.337***	-0.395***
	(-3.66)	(-5.39)	(-3.56)
low_innov	0.000933	-0.106	-0.0710
	(0.02)	(-1.21)	(-0.68)
Group: *Persistent HG*			
ros	0.691	-0.569	-0.837
	(0.43)	(-0.58)	(-0.39)
roa	-1.573	1.196	1.803
	(-0.84)	(0.70)	(0.97)
ie/s	0.790	-0.311	-10.63
	(1.24)	(-0.40)	(-1.18)
ltd/ass	-0.989	0.638	1.728
	(-1.59)	(1.63)	(1.60)
log(lp)	-0.165	-0.274	-0.411
	(-1.17)	(-1.75)	(-1.75)
low_innov	0.0561	-0.365*	-0.276
	(0.53)	(-2.14)	(-1.32)
χ^2	49.71***	51.79***	24.63**
log pseudolikelihood	-4137.41	-2262.70	-1361.52
Observations	8544	8496	2966

high-growth firms (HG) as baseline group

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Multinomial probit - Pavitt sectors

Variables	(1) Italy	(2) Spain	(3) France
Group: *Other firms*			
ros	2.589	1.154	1.588
	(3.80)	(1.93)	(1.56)
roa	-3.155***	-0.0157	-0.617
	(-3.46)	(-0.02)	(-0.79)
ie/s	-2.396	-1.342	-5.670
	(-1.34)	(-0.95)	(-1.53)
ltd/ass	0.623	-0.553	-0.0447
	(1.07)	(-2.76)	(-0.06)
log(lp)	-0.229***	-0.342***	-0.413***
	(-3.63)	(-5.40)	(-3.69)
Pavitt_SB	0.0637	0.307	-0.0337
	(0.53)	(1.12)	(-0.16)
Pavitt_SS	-0.0119	-0.00630	-0.143
	(-0.12)	(-0.05)	(-1.02)
Pavitt_SD	-0.00997	-0.0804	-0.151
	(-0.19)	(-1.18)	(-1.65)
Group: *Persistent HG*			
ros	0.700	-0.454	-0.653
	(0.44)	(-0.48)	(-0.31)
roa	-1.615	1.048	1.739
	(-0.87)	(0.64)	(0.94)
ie/s	0.774	-0.455	-12.74
	(1.21)	(-0.59)	(-1.36)
ltd/ass	-0.978	0.596	1.651
	(-1.58)	(1.53)	(1.52)
log(lp)	-0.162	-0.280	-0.433*
	(-1.14)	(-1.78)	(-1.97)
Pavitt_SB	0.331	0.555	-0.0432
	(1.56)	(1.26)	(-0.10)
Pavitt_SS	-0.186	-0.191	-0.625
	(-0.79)	(-0.61)	(-1.76)
Pavitt_SD	0.0561	-0.317*	-0.324
	(0.54)	(-2.10)	(-1.77)
χ^2	52.69***	55.21***	30.38**
log pseudolikelihood	-4135.76	-2260.97	-1359.26
Observations	8544	8496	2966

high-growth firms (HG) as baseline group

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Multinomial probit - Size and Age

Variables	(1) Italy	(2) Spain	(3) France
Group: *Other firms*			
ros	2.639	1.060	0.966
	(1.84)	(1.78)	(0.96)
roa	-3.514***	0.551	0.302
	(-3.81)	(0.66)	(0.41)
ie/s	-1.394	-0.820	-3.457
	(-1.17)	(-0.66)	(-0.91)
ltd/ass	-0.176	-0.110	-0.0644
	(-0.60)	(-0.53)	(-0.09)
log(lp)	-0.196**	-0.485***	-0.428***
	(-3.22)	(-7.40)	(-3.95)
age	0.0163***	0.0279***	0.0130***
	(8.16)	(5.90)	(3.76)
log(size)	0.331***	0.148***	0.167***
	(12.66)	(4.47)	(4.70)
Group: *Persistent HG*			
ros	0.556	-0.508	-1.119
	(0.38)	(-0.56)	(-0.49)
roa	-0.760	0.890	1.391
	(-0.43)	(0.58)	(0.82)
ie/s	0.992	-0.534	-15.20
	(1.14)	(-0.55)	(-1.59)
ltd/ass	0.0124	0.437	1.415
	(0.02)	(1.10)	(1.42)
log(lp)	-0.279*	-0.240	-0.315
	(-2.45)	(-1.77)	(-1.53)
age	-0.0103	-0.00745	-0.0195
	(-1.94)	(-0.48)	(-1.91)
log(size)	-0.310***	-0.152	-0.00823
	(-5.71)	(-1.90)	(-0.11)
χ^2	474.67***	148.26***	83.14***
log pseudolikelihood	-3866.23	-2181.29	-1316.02
Observations	8544	8496	2966

high-growth firms (HG) as baseline group
t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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

Country	HG	PHG	ROA	ROS	IE/S	LTD/ASS	LP
Age classes							
Young							
IT	194	17	0.8851	0.3872	-0.6410	-1.4328	-0.6945
ES	215	18	-0.3833	-0.2603	0.2260	-0.4715	-0.6269
FR	77	4	-0.6703	-1.7749	0.2085	0.4722	0.1928
Medium							
IT	603	59	-1.3216	-0.5460	1.5731	-0.0835	1.2916
ES	397	23	-0.3874	-0.9565	0.5188	1.3045	-0.8245
FR	88	9	-1.4070	-0.3525	-0.0460	0.5760	-1.5698
Old							
IT	440	38	0.2727	-0.0836	1.0050	0.3337	-0.0909
ES	88	9	-1.4070	-0.3525	-0.0460	0.5760	-1.5698
FR	130	11	-0.9947	-0.8352	1.7633	0.3139	-0.7266
Size classes							
Small							
IT	742	76	-1.1992	-0.7146	0.6235	-1.9230	-1.3930
ES	629	49	-0.7769	-0.7260	0.2942	-0.6375	-1.9366
FR	316	21	2.2612*	1.1726	-0.3185	1.3492	0.4365
Medium							
IT	442	41	0.7347	0.6179	0.5316	0.0110	0.1076
ES	61	7	-3.9036**	-1.6557	0.4515	0.9525	-0.3546
FR	77	10	-0.6371	0.3521	2.3366*	0.7412	-0.0832
Large							
IT	60	5	-0.5100	-0.1123	0.2954	1.3119	-0.3601
ES	16	2	-5.9029***	-0.6810	0.5866	-0.0530	-1.9380
FR	22	1	-	-	-	-	-

Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

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