What 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 production efficiency, profitability and financial status as the central channels through which firms can survive, grow and eventually achieve outstanding growth performance. Does the same conceptual framework provide a convincing explanation of persistent corporate high-growth? Exploiting panels of Italian, Spanish, French and UK 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 different financial conditions than firms that only exhibit high, but not persistent, growth performance. The finding is robust across countries, across manufacturing and services, and also controlling for firm innovation, age and size.

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1 Introduction

Among the many private companies that populate developed economies it is typically possible to identify, within a given time window, 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; Stangler, 2010). On the one hand, managers and consultants are interested in understanding the "best-practices" which are responsible for superior firm performance and seek 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 and fostering of macroeconomic growth.

There is a vast empirical literature on high-growth companies, that links the occurrence of high-growth events to 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 the degree of firm innovativeness. This literature focuses on the identification of the causes and conditions that lead a company to outperform its competitors in a specific, relatively short, period of time.

In this paper we offer a different perspective. Instead of searching for the determinants of high-growth at a given point in time, we want to identify the factors that make a firm a *persistent* high-growing firm. The motivation for this shift of focus rests in the consideration that high-growth performances have a more relevant economic impact and turn more interesting to practitioners and promising to policy makers, if they are long lasting and persistent. This is indeed the kind of growth behavior that is likely connected with the presence of structural comparative advantages and exceptional capabilities inside the firm. 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 firms sporadically respond to market shocks, other 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 the persistence of firm growth rates, with mixed results, the study of the persistence in high-growth patterns is only of very recent development. Existing studies limit the attention to the exploration of demographic characteristics of firms, such as size, age or sector of activity. We instead want to address whether persistent high-growth is related to superior operating capabilities. Our key question is whether persistent high-growth firms differ in terms of productivity or profitability with respect to firms that display "spurts" of high-growth, but are not able to consistently replicate high-growth performance over a longer period of time. Answering this question has relevant policy implications, since one wants to understand whether firms able to sustain high-growth over time are also those which can increase the overall efficiency and competitiveness of sectors and countries. We do not know of previous studies making such an attempt.

Theories of firm-industry dynamics with heterogeneous firms, 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 the models specifically addresses the issue of the relative abundance of high-growth firms and their behavior over time, they all relate growth rates differentials across firms to the presence of competitive advantages due to structural factors, which influence firm performances over a relatively long period of time. Persistent productivity or profitability differentials hint at an equally persistent growth dynamics, as more efficient firms are predicted to progressively erode market shares from competitors.

The relative abundance of internal vs. external finance plays also an important role in these dynamics. Indeed, despite the fact that growth events can be considered as a risky enterprise by potential lenders, firm expansion must often rely upon external finance, especially when growth is extraordinary fast and sizable. Theoretical models do not provide a definite conclusions about the role of external finance on high-growth, since different frameworks assume different market structure for the incumbent firms, which in turn imply very different potential profitability patterns and risk levels. Still, financial factors are affected by the actual or expected operating capability of the firm and, hence, they have to be included in the analysis in order to avoid a potentially relevant source of endogeneity bias.

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

Our findings are challenging for both academic scholars and policy makers. Indeed, we do confirm that some structural characteristics, and productivity in particular, are significantly associated with high-growth. However, we do not find evidence of any systematic difference between high-growth and persistent high-growth firms, nor in terms of operating efficiency, neither in terms of the other considered dimensions. None of these dimensions seems to work in sustaining high-growth performance repeatedly over time. The same pattern is invariant across manufacturing and services, suggesting minor role of sectoral specificities, and it is also stable 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 firm-level innovation, disaggregated analysis by size and age, and alternative estimation methodologies.

2 Background literature and motivation

Our study is directly related to the empirical literature on 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 performance, a stream of literature focuses on the role of factors external to the firm, such as institutions, geography, sectoral or broadly speaking macro-level variables. 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.

The empirical investigation of the micro-level determinants of high-growth is more recent. Beyond confirming that high-growth occurs most often among young and small firms, most studies has somewhat disproportionately focused on innovation-related drivers. Coad and Rao (2008) link R&D and patenting to sales growth of incumbent firms in high-tech sectors, finding that innovation activity 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. Segarra and Teruel (2014) show, on Spanish data, that internal R&D investment positively affects the probability to be a high-growth firm, while external R&D does not. Finally, Colombelli et al. (2014) investigate whether the characteristics of the knowledge base (i.e. variety, coherence, and similarity) impact on growth dynamics of a set of European publicly traded companies. The evidence supports the conjecture that high-growth firms tend to adopt exploration rather than exploitation strategies, therefore stimulating the creation of new technological knowledge.

As the influential contributions by Delmar et al. (2003); **?** have 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. As a matter of fact, there exist several types of high-growth patterns, which in turn differ by demographic characteristics such as size, industry affiliation or firm age, and by type of governance. Differences are sharp, ranging from "super absolute growers", which are typically small- and medium-sized firms operating in knowledge intensive manufacturing industries, to the "erratic one-shot growers", which are more common among small-sized firms in low-technology service sectors. It is then plausible to expect that the investigation of the determinants of high-growth can lead to different results, according to the definition of high-growth which is adopted. This consideration motivates 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, which are essentially focused on the explanatory factors of short-run and sporadic high-growth events, we want to include the persistence of such high-growth dynamics into the picture. 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 equilibrium framework 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 models, while it 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 conditions, grant to more productive firms the access to the resources needed to invest and pursue further growth, possibly with some time lag.

Although the models do not directly discuss the emergence and persistence of high-growth firms, one can derive a common set of implications relevant to our study.

First, the shared core mechanism underlying survival, selection and growth dynamics points at efficiency and profitability as the candidate key drivers of high-growth. Since the latter capture the differential competitive advantages of firms, in turn driving firms' differential ability to survive and grow, we should expect high-growth firms to be more productive and more profitable than firms displaying normal growth patterns. Second, there is a consensus that financial conditions and access to external finance must be included in the analysis, also because they can be endogenous to productivity or operating profits. It is difficult to draw definite predictions, however. In fact, on the one hand, availability of internal resources (profits or cash flow) can ease the need for and dependence from external finance. But sounder financial conditions also imply a superior capability to meet debt servicing and, eventually, they can also associate to a larger debt exposure, *ceteris paribus*. Which effect eventually prevails is uncertain a priori, and it also depends from the capability of the credit market to correctly select the appropriate growth prospects.

Third, and even more relevant for us, the models are uninformative about whether the kind of structural or financial drivers that eventually fosters high-growth can also be considered as drivers of persistent high-growth. Some scholars have even advanced the hypothesis that randomness (or "mere luck") is the most appropriate account of firms' persistent success (Barney, 1997).

Against this lack of a clear guiding theoretical framework, the empirical literature has not dedicated much attention to the identification of the determinants of persistence in high-growth performance. Traditionally, firm growth studies looks at the average persistence, within a sector or a sample of firms, but not at persistence of high-growers. A long tradition of works estimate the autocorrelation structure in the growth process, mostly with the aim 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).[1]

It is only recently that empirical research considers the degree of persistence in the entire distribution of the growth rates. Quantile autoregression or transition probability matrices in this context allow to uncover if there is persistence in the top-growers. Coad (2007) and Coad and Hölzl (2009) do observe some persistence in the top-tail of the growth distribution, with small high-growth firms displaying negative autocorrelation, whereas large and established companies achieving smoother dynamics. Conversely, Capasso et al. (2013) conclude that persistent outperformers are more often present among micro firms. Yet, other studies cast doubt on the very existence of persistent high-growers. Daunfeldt and Halvarsson (2012) claim that high-growth firms are basically "one-hit wonders", and document that firms experiencing strong job losses in one period are most likely to become high-growth units in the next period. The findings in Hölzl (2014) confirm that most of high-growth firms do not replicate their high-growth performance over time, and show that the degree of persistence might also depend upon the criterion adopted for the identification of such companies.

Overall, the state of the art is that we do not have no attempts to address if more structural, economic or financial, factors are distinguishing features of persistent high-growth companies, above and beyond mere demographic characteristics such as size, age and industry affiliation. This is the key contribution we seek to offer in this article.

[1]In between, positive serial autocorrelation is found by Geroski et al. (1997) on a panel of UK quoted firms, Wagner (1992) for German manufacturing companies, Weiss (1998) for the Austrian farm sector, and Bottazzi and Secchi (2003) for 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. 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.

3 Data and identification of persistent high-growth firms

In this Section, we present the data, our definitions of high-growth and persistent high-growth firms, and the proxies we use to measure firm characteristics. A key point is that the identification of persistence in high-growth performance requires a reasonably long period of time over which firm growth is evaluated. Our strategy is to divide the time span available in the data into two periods, and exploit the first period to measure "initial" firm characteristics, which we next seek to map into high-growth, persistent high-growth or other growth dynamics over the second period.

Sources and sample

We draw 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 in all sector of activity, covering all European countries. We have access to data on Italy, Spain, France and the UK. 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; 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.[2] All the firms are classified according to their sector of principal activity, disaggregation up to 2-digits of NACE 2008 classification. The present study considers both manufacturing and services, covering a final sample of 55,454 firms.[3]

Spain has the higher number of observations followed by Italy, France and the UK. The number of small-medium enterprises (with less than 250 employees), covers approximately 95% of the entire sample. More than 60% of the sample is represented by firms belonging to Services. A screenshot of the data by countries and sectors is in the Appendix.

Definition of high-growth and persistent high-growth

The obvious preliminary step in the analysis is to choose a definition of high-growth firms and to design a strategy to identify persistent high-growth performance. 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 size proxy is chosen. At the same time, studies looking at growth rates autocorrelation (on the average or within quantiles) do not provide a criterion to identify persistent high-growth

[2]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 high-growth firms with "other firms", but rather high-growth-and-surviving firms with other-and-surviving firms. In fact, it could be the case that this distinction does matter in some instances. Due to the nature of our database, however, we are not in the position to test this hypothesis. We omit any further reference to this issue in what follows.

[3]The sector of principal activity in the AMADEUS dataset is time-invariant, measured in the last available year. Manufacturing includes section C, while Services include sections G, H, I, J, K, L, M, N, R, S.

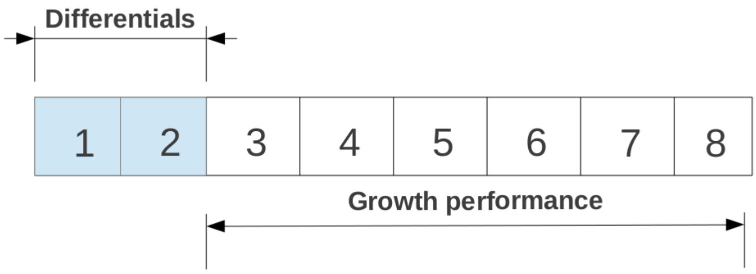

Figure 1: Partitioning of the sample time-period. Differences in firm attributes are measured in the first two years (2004-2005), while growth patterns are evaluated over the subsequent six years (2006-2011).

enterprises, beyond sharing the basic intuition that these firms must experience high-growth performance – however defined – consecutively for some years.

Against this background, we implement the following choices. First, we measure annual growth of firm i in year t, in terms of the log difference

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

where

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

with firm size S_{it} measured as either sales or number of employees, and the sum computed over the N firms populating the same (2-digit) sector. In this way firm size and, thus, 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.

In the data, both employment and sales growth rates distributions display the usual fat-tails shape already found in previous studies. In case of employment growth, maximum likelihood estimates of the shape parameter b of a Power Exponential distribution (see Bottazzi and Secchi, 2006) range indeed from 0.45 for French firms to 0.87 for UK firms. The distributions of sales growth rates have b very close to 1 in all countries, thus close to a Laplace distribution. The results are stable over the years of the sample period.

Given a sample period of 8 years, we reserve the first two years (2004-2005) to measure the firm characteristics that we want to map into growth performance, while we exploit the last six years (2006-2011) to identify firms displaying different "growth status" (see Figure 1). To identify high-growth (HG) firms, we compute the total growth rates experienced by each firm in terms of both sales and employment over the six years spanning the second part of the sample period, and then define as HG firms those companies falling into the top 10% of the total growth rates distribution, in terms of at least one of the two growth measures. To define persistent high-growth (PHG) firms, we examine the annual growth rates of each firm, again over the last six years of the sample period, and define as persistent high-growth companies those firms falling for at least four (out of five) years into the top 10% of the yearly cross-sectional distribution of either sales or employment growth (or both). We then assign all firms not passing the two criteria to a residual category of "other firms".

With our definition we expect to have from 10% to 19% of firms classified as HG firms. The lower bound corresponds to the case of perfect cross-correlation between employment growth and sales growth, whereas the upper bound corresponds to the case in which the two growth rates measures are uncorrelated. At the same time, under the hypothesis of serially uncorrelated growth rates, we expect the fraction of PHG firms to be in between 0.045% (for perfect cross-correlation between sales growth and employment growth) and 0.65% (for no cross-correlation).

Table 1: # of High-growth and persistent high-growth firms, Manufacturing

	Italy			Spain			France			UK		
NACE	**Total**	**HG**	**PHG**	**Total**	**HG**	**PHG**	**Total**	**HG**	**PHG**	**Total**	**HG**	**PHG**
10	724	117	14	927	129	8	415	65	4	140	19	1
11	143	21	2	173	16	1	58	10	2	38	4	0
12	2	1	0	2	0	0	0	0	0	2	0	0
13	507	67	6	310	38	1	68	10	0	28	3	0
14	280	63	8	179	30	0	41	11	1	15	3	0
15	268	47	4	206	35	2	31	4	0	1	0	0
16	176	24	4	386	65	6	186	28	1	23	2	0
17	249	23	1	135	12	1	57	7	1	46	5	0
18	145	21	0	506	67	2	187	22	2	64	8	2
19	38	7	1	7	1	0	5	0	0	8	1	0
20	447	64	5	265	26	3	112	18	1	116	17	1
21	114	20	1	29	1	1	22	4	0	34	4	0
22	553	78	2	350	50	3	196	25	3	70	6	1
23	459	72	5	516	109	6	169	25	1	47	6	1
24	363	50	3	194	27	0	37	3	1	34	3	0
25	1422	178	24	1511	263	10	615	78	8	166	20	3
26	279	44	6	92	14	2	111	20	2	88	17	2
27	404	66	8	160	22	5	69	8	1	55	11	1
28	1231	178	22	442	49	6	202	22	9	139	18	4
29	173	28	1	162	30	2	69	11	2	44	2	2
30	88	16	5	28	9	0	27	4	0	28	6	0
31	310	42	7	425	73	3	80	13	0	31	4	2
32	197	29	7	169	26	4	94	13	0	184	22	3
33	115	19	2	363	50	6	290	48	3	56	9	1
Total	8687	1275	138	7537	1142	72	3141	449	42	1457	190	24

Of course, if there is perfect serial correlation in growth rates, then all HG firms are also PHG firms (and the above upper and lower bounds apply).

The choice to consider both sales and employment growth in the definition of HG and PHG firms allows for a multidimensional description of the growth process, responding 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. Indeed, sales is more a proxy of success on the market, while employment is more related to establishing capacity.[4] Definitions based on a single size indicator can considerably reduce the number of PHG firms, undermining the reliability of the empirical analysis. We have however verified that our main empirical findings do not change if we identify HG and PHG firms based exclusively on employment or exclusively on sales.

The strategy to identify HG firms through annualized average growth over some years is in line with most of the literature, and reflects the consideration that growth is quite unstable over time, so that one single big growth shock in one year is not enough to capture true high-growers. Depending on the study, the number of years considered may vary from 3 to 6 years, but the main idea is common to the vast majority of previous works. There is instead less consensus on whether the threshold employed to distinguish high-growth from "normal growth" needs to be in absolute value (for instance, defining as HG a firm that hires at least 100 employees) or in relative terms, that is looking at percentage growth over time. Our definition implicitly follows the latter approach. Absolute growth implies a bias towards larger firms, whereas the percentage measure allows smaller firms to enter the HG group. Also questionable is our choice to consider the top 10% of annualized average growth. We have experimented with other definitions appearing in the literature (top 15%), and the main conclusions from the empirical analysis do not change.

Given the lack of a precise definition of PHG firms in previous studies, our identification criterion balances between the aim to capture firms that outperform other firms continuously

[4]Sales and employment are indeed the most frequently chosen size proxies in the literature. 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 of the industry (as opposed to total assets). Also notice that the inter-sectoral comparability is improved by the use of the normalized shares defined in Equation (2).

Table 2: # of High-growth and persistent high-growth firms, Services

	Italy			Spain			France			UK		
NACE	**Total**	**HG**	**PHG**	**Total**	**HG**	**PHG**	**Total**	**HG**	**PHG**	**Total**	**HG**	**PHG**
45	773	82	10	1596	178	7	1115	137	8	337	27	0
46	2949	417	54	5092	776	99	2122	267	40	555	56	7
47	782	106	13	3627	530	42	1753	245	26	202	22	7
49	320	40	7	992	126	11	466	66	3	147	13	1
50	22	4	1	32	5	0	6	0	0	15	2	0
51	11	1	1	5	0	0	1	0	0	24	4	0
52	292	43	4	252	39	2	94	11	4	74	11	1
53	4	1	0	22	4	0	3	1	0	5	1	0
55	162	22	0	443	34	2	312	22	3	112	8	0
56	105	10	2	1171	151	7	456	65	5	73	8	0
58	84	10	4	137	22	2	83	18	1	61	9	0
59	16	3	0	43	9	2	31	3	0	21	3	0
60	22	2	0	29	7	0	6	0	0	7	2	0
61	18	5	0	68	11	1	16	4	0	42	10	1
62	184	33	1	237	40	6	119	21	4	135	30	3
63	72	12	2	15	1	0	20	3	0	15	2	0
64	41	10	3	33	6	0	71	22	5	157	19	4
66	17	1	1	40	6	1	8	1	0	29	6	2
68	160	27	6	218	84	13	75	42	6	61	10	2
69	70	6	1	298	21	2	57	4	0	11	2	0
70	155	32	4	125	25	1	89	17	4	282	41	5
71	99	14	9	271	45	11	150	30	3	46	6	1
72	23	4	1	20	2	0	16	2	0	15	2	1
73	85	17	1	202	43	5	68	11	1	39	6	1
74	51	10	4	188	49	6	34	2	3	44	6	2
75	0	0	0	29	5	0	1	0	0	1	0	0
77	43	7	0	174	41	6	82	12	2	81	14	1
78	10	5	0	8	1	0	7	0	1	55	14	1
79	64	12	2	117	23	3	10	1	0	32	6	0
80	37	3	0	49	8	0	15	1	1	10	1	0
81	82	17	3	234	42	2	204	26	5	26	2	1
82	91	19	3	86	14	3	78	15	2	199	37	5
90	15	3	2	40	7	1	24	8	1	9	1	0
91	6	0	0	6	4	0	11	1	0	1	0	0
92	6	1	0	87	14	1	39	1	0	10	2	0
93	74	13	5	176	31	0	52	7	1	40	4	0
94	0	0	0	6	0	0	0	0	0	8	1	0
95	28	5	0	103	21	1	35	4	1	3	0	0
96	52	6	0	239	26	4	282	30	3	102	12	2
Total	7025	1003	144	16510	2451	241	8011	1100	133	3086	400	48

over a reasonably long number of years, and the time constraint imposed by the available data. We have checked that the results presented in the following empirical analysis do not change if we apply a less stringent criterion where persistent high-growth firms are defined as firms passing the 10% threshold for just 3 out of 5 years. On the other hand, being more restrictive and imposing that PHG firms pass the threshold in all years, substantially reduces the number of PHG firms, making the statistical analysis unfeasible.

Tables 1 and 2 show the number of HG and PHG firms by country and sectors, as resulting from the identification criteria we adopted to identify growth status over the period 2006-2011. The incidence of HG firms is comparable across countries, varying between 12.9% and 15.1% of the total sample. These numbers are compatible with non-zero cross-correlation between sales and employment growth. The number of PHG companies is small, ranging from 0.9% to 2% of the total sample in the different countries. This is in line with previous studies, even when adopting different identification criteria, and suggests some degree, although not perfect, of serial correlation in employment and sales growth rates. We also observe a relatively higher incidence of PHG firms within services than within manufacturing.[5]

Firm characteristics

We map growth status into a set of indicators of structural performance including productivity, profitability and financial condition, together with the more traditionally investigated characteristics in terms of size and age.

[5]The number of PHG firms increases, but it never exceeds the 5% of the total population if we consider 3 out of 5 years as the identification criterion for the definition of PHG firms.

Table 3: Descriptive statistics

	MANUFACTURING						SERVICES					
	2004		**2007**		**2010**		**2004**		**2007**		**2010**	
Variable	**Mean**	**Std**	**Mean**	**Std**	**Mean**	**Std**	**Mean**	**Std**	**Mean**	**Std**	**Mean**	**Std**
Italy												
log(TFP)	4.62	0.56	4.76	0.55	4.69	0.58	4.5346	0.7425	4.6905	0.7444	4.6353	0.7503
ROA	0.0235	0.0542	0.0302	0.0564	0.0190	0.0555	0.0207	0.0678	0.0255	0.0646	0.0184	0.0646
IE/S	0.0136	0.0201	0.0153	0.0222	0.0107	0.0140	0.0136	0.0326	0.0156	0.0326	0.0114	0.0396
LEV	0.6097	0.1991	0.6193	0.2000	0.5589	0.2070	0.6746	0.2129	0.6760	0.2084	0.6235	0.2250
Age	22.92	14.79	25.92	14.79	28.92	14.79	19.98	14.82	21.98	14.82	23.98	14.82
Size (sales)	24057.56	125718.60	30555.89	153283.90	28630.10	121112.50	27633.70	125823.70	33886.27	140855.40	35523.14	152103.80
Size (no. employees)	85.73	256.60	91.82	288.71	89.76	292.12	106.49	1555.98	100.35	518.16	109.49	563.37
Spain												
log(TFP)	3.64	0.61	3.83	0.58	3.74	0.62	3.5769	0.6899	3.7907	0.6893	3.7051	0.7065
ROA	0.0335	0.0879	0.0393	0.0741	-0.0096	0.1336	0.0365	0.0934	0.0402	0.1118	-0.0004	0.1266
IE/S	0.0145	0.0216	0.0171	0.0190	0.0189	0.0293	0.0127	0.0297	0.0157	0.0358	0.0167	0.0448
LEV	0.6493	0.3031	0.5328	0.2596	0.5863	0.3309	0.6857	0.3029	0.5730	0.3195	0.6177	0.3828
Age	14.24	11.20	17.24	11.20	20.24	11.20	11.96	9.07	13.96	9.07	15.96	9.07
Size (sales)	13144.34	236536.90	16900.90	333398.00	15330.09	322342.90	13398.45	433976.10	19305.39	640646.50	20100.02	710875.00
Size (no. employees)	51.52	816.53	57.24	1161.73	52.91	1115.56	55.47	1561.01	71.55	2177.18	77.15	2430.92
France												
log(TFP)	4.18	0.55	4.30	0.54	4.29	0.55	4.2131	0.6195	4.3182	0.6224	4.3485	0.6402
ROA	0.0498	0.0978	0.0594	0.1007	0.0396	0.1128	0.0583	0.1182	0.0632	0.1067	0.0492	0.1220
IE/S	0.0074	0.0089	0.0073	0.0096	0.0062	0.0201	0.0079	0.0164	0.0071	0.0126	0.0060	0.0135
LEV	0.5346	0.2122	0.5705	0.2250	0.5361	0.2670	0.5911	0.3069	0.6216	0.2768	0.5918	0.3476
Age	22.39	19.14	25.39	19.14	28.39	19.14	17.61	14.98	19.61	14.98	21.61	14.98
Size (sales)	18866.41	196887.50	22486.79	238035.60	21827.05	263363.70	30415.01	551751.80	39785.44	730391.10	43108.86	820173.70
Size (no. employees)	86.62	715.23	88.99	784.36	87.65	835.33	163.06	3132.35	227.27	4484.88	225.69	4671.12
UK												
log(TFP)	3.93	1.95	4.03	1.31	4.02	1.34	4.9161	1.1644	5.0666	1.1777	4.9549	1.1892
ROA	0.0470	0.0926	0.0537	0.1024	0.0557	0.1018	0.0490	0.1216	0.0570	0.1166	0.0428	0.3575
IE/S	0.0109	0.0154	0.0136	0.0186	0.0115	0.0216	0.0185	0.0421	0.0242	0.1362	0.0170	0.0438
LEV	0.5945	0.2449	0.5686	0.2661	0.5290	0.2601	0.6673	0.3492	0.6485	0.4025	0.6140	0.3703
Age	30.69	25.99	33.69	25.99	36.69	25.99	24.16	23.53	26.16	23.53	28.16	23.53
Size (sales)	179168.80	1106028.00	210478.00	1317031.00	212923.40	1462093.00	287814.70	1865298.00	323652.50	2034431.00	338985.20	2415635.00
Size (no. employees)	781.15	4306.20	869.86	5197.60	850.39	5342.37	1632.55	11239.11	1750.51	11613.20	1836.24	12900.66

Notes: Annual mean and standard deviation (Std) of the main firm characteristics in 3 reference years. Total Factor Productivity (TFP) via the modified Levinshon-Petrin estimator in Wooldridge (2009). Return on Assets (ROA) as operating margins-to-assets ratio. Coverage ratio as interest expenses over sales (IE/S). Leverage (LEV) as total debt over total assets. Age is computed from year of foundation. Sales are in thousands of Euros, and number of employees in units.

We compute Total Factor Productivity (TFP) as the residual of production function estimation performed through the IV-GMM modified Levinsohn-Petrin estimator proposed in Wooldridge (2009).[6] As our profitability proxy, we consider an index of Return on Assets (ROA), defined as operating margins over total assets. Financial conditions are taken into account by looking at two indicators capturing different dimensions of financial status: a 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 standard measure of leverage (LEV), computed as the ratio between total debt and total assets. Age is computed exploiting information on the year of foundation. Lastly, we proxy for size through annual sales in distributional and regression analysis, and we use employment to define the size-classes in the analysis of Section 7.

Table 3 provides basic descriptive statistics in three reference years. The broad picture reflects well known differences across the countries. TFP displays indeed similar rankings across countries, with UK, France and Italian companies displaying higher average efficiency than Spanish counterpart. Notice that UK service firms are characterized by the highest average value of TFP. Concerning profitability, the average ROA is higher in the UK and France, in all years, while similar across the other two countries. The pattern is robust across manufacturing and services. 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 even if more

[6] The estimates are performed pooling firms within the same 2-digit level sector, taking number of employees and fixed tangible assets as measures of labour and capital inputs, respectively, and value added as the proxy for output, while we use the cost of material inputs as instrument to control for endogeneity of labour inputs. Alternatively, we have also considered a standard labour productivity index computed as the ratio between value added and number of employees. Results are in line with those presented along this article.

modest in the UK and particularly marked in Spain. The financial ratios display interesting patterns across sectors and countries. In manufacturing, French and UK firms are relatively more solid on average 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. Similar patterns appear in Services, but here average leverage is higher than in manufacturing, in all countries, suggesting larger debt exposure of service firms. Average firm size in terms of sales is definitively larger in the UK, similar across Italy and France, while Spanish firms are smaller on average. UK firms are also bigger in terms of employment, again with the average Spanish firms being smaller than the average French and Italian companies in the sample. This may also be part of the explanation of the comparatively lower average productivity observed for Spanish firms. Finally, notice the differences in age, with Spanish firms on average younger, reflecting the typical structure of the economy. The average age of the firms (above 10 years old in all countries) is obviously influenced by the choice to only look at incumbent firms along the considered time window.

4 Distributional analysis

We start by assessing statistical differences in the empirical distributions of firm characteristics across the three groups of HG, PHG and "other" firms.

To reduce the impact of possible outliers, we compute the average of the variables (ROA, financial indicators, TFP, age and size in terms of sales) over the two initial years which are not used to identify HG and PHG patterns. On this set of variables, we make pairwise comparisons across the three groups of firms, by applying the Fligner and Policello (1981) procedure (hereafter, FP) to test stochastic equality between two empirical distributions. While usual tests try to assess differences up to a shift of location (in mean or in median), the FP test looks at the stochastic dominance between two compared samples, asking which of the two compared distributions is statistically more likely to have more probability mass in the right part of the support. Because of its very mild assumptions, the test is particularly suitable in case of uneven samples, it does not require equality of variances, and it allows for asymmetries. All these features are found in our data.[7]

We take the HG firms as the reference category, so that a statistically significant and positive (negative) FP statistic indicates that HG firms have larger (smaller) probability to display a larger value of the considered variable, with respect to the compared group of "other" or PHG firms. The analysis is run separately by manufacturing and services, within each country or pooling across countries. Since univariate analysis is likely to be polluted by unobserved heterogeneity, we only discuss highly significant (more than 1%) differences.

In Table 4 we compare HG firms versus "other firms". Our first noticeable finding is that demographic characteristics are confirmed to distinguish outstanding growing firms. Indeed, in agreement with the literature, HG firms are smaller and younger in distribution. The result is generally valid in our data, across countries and sectors. The exception is the UK, where HG and other firms are statistically equal in terms of age in manufacturing, and in terms of size in services.

The picture is more nuanced when we turn to more structural characteristics. First, we find a very weak association of high-growth performance with profitability. Indeed, the null of equality is rejected only for Italian manufacturing firms, with a positive FP statistic in

[7]A drawback of the FP test, common to other non-parametric tests, is the need to have more data points to achieve the same power of basic tests for differences in mean. We have verified that our conclusions from the FP test, however, remain valid if we use a standard two-sample Student's t test for equality of the mean across samples with unequal variances, and also if we employ a Wilcoxon-Mann-Whitney test for equality of medians.

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

	Country	#Other firms	#HG	ROA	IE/S	LEV	log(TFP)	AGE	log(SIZE)
Manufacturing									
FP test	Pooled	17490	3056	2.330	3.127*	11.251**	-0.796	-18.210**	-8.585**
	IT	7274	1275	2.564*	2.207	9.035**	-2.941*	-12.886**	-8.068**
	ES	6323	1142	0.252	2.453*	6.442**	0.749	-10.979**	-4.789**
	FR	2650	449	1.619	0.225	3.689**	0.083	-8.494**	-3.779**
	UK	1243	190	0.902	-0.079	0.316	1.500	-1.701	-2.957*
Services									
FP test	Pooled	29112	4954	2.032	1.998	8.400**	0.917	-19.426**	-9.098**
	IT	5878	1003	0.666	0.223	4.374**	-0.659	-11.546**	-7.355
	ES	13818	2451	1.139	0.817	4.915**	3.562**	-11.743**	-6.777**
	FR	6778	1100	2.032	2.877*	4.083**	-0.664	-8.059**	-4.078**
	UK	2638	400	1.798	-0.309	2.946*	-0.851	-7.112**	-2.514

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

agreement with the prediction that HG firms are more profitable. No differences against other firms are detected in all other countries, irrespective of the sector. Second, we find similarly lacking evidence of significant differences in terms of efficiency. The exceptions in this case are in Italian manufacturing, where HG firms have lower TFP in distribution, and in Spanish services, where HG firms appear as more efficient than the group of other firms. The negative sign for Italian manufacturing firms is somewhat at odds with theoretical predictions, but it could be driven by the strong correlation between capital intensity and size. The multivariate regression analysis in the following sections will shed light on this conjecture. Third, moving to financial factors, the estimates on the IE/S ratio provide mixed results. HG firms active in Spanish manufacturing and in French services have a larger share of sales "absorbed" by annual debt servicing, while we do not observe statistically significant differences with respect to the group of other firms in all the other country-sector combinations. Conversely, we find robust evidence that HG firms differ in terms of leverage. In all cases, with the only exception of UK services, we obtain strongly significant and positive statistics, implying that HG firms feature an heavier reliance on debt as compared to own assets. Since both leverage and IE/S ratio are here measured ex-ante, in the years before the actual HG status is realized, the implication is that will-be HG firms do have access to external finance, so they are not completely credit rationed, but have to pay more for it.

Overall, we find signals that structural characteristics matter, but the evidence is not that conclusive as one could expect from theory. Beyond age and size, only a relatively high degree of ex-ante indebtedness is clearly standing out as a distinguishing feature of high-growth firms. Variation of this picture across sectors and countries is minor.

Even more striking, structural characteristics play an even weaker role in the comparison between HG and PHG firms, reported in Table 5. Profitability and the IE/S ratio never display statistically significant differences across the two groups of firms, in all countries and across both manufacturing and services. Second, PHG firms tend to be less productive than HG firms in Italian manufacturing, while in all other country-sector combinations PHG and HG firms have statistically identical TFP distribution. Third, we can say that leverage displays some, albeit very limited, discriminatory power. PHG firms are more indebted than HG firms, in proportion to their total assets, in Italy and in the UK in manufacturing, and if we pool the data altogether in services. Finally, the results cast also doubts on the role of size and age. In manufacturing, PHG firms tend to be younger and smaller in Italy and Spain, while we cannot

Table 5: Distributional comparisons - HG vs. PHG firms

	Country	#Other firms	#HG	ROA	IE/S	LEV	log(TFP)	AGE	log(SIZE)
Manufacturing									
FP test	Pooled	3056	276	1.323	-1.594	-4.365**	1.978	4.794**	3.784**
	IT	1275	138	2.029	-1.967	-3.407**	4.870**	3.861**	7.732**
	ES	1142	72	0.156	-0.944	-1.914	2.284	4.679**	3.742**
	FR	449	42	-0.251	0.323	-2.002	0.899	1.523	1.731
	UK	190	24	-0.555	-0.832	-3.012*	-0.557	2.040	0.375
Services									
FP test	Pooled	4954	566	0.773	-0.849	-3.458**	0.148	5.129**	1.933
	IT	1003	144	1.579	-1.177	-2.427	2.532	2.366	3.330**
	ES	2451	241	0.012	-1.469	-1.857	1.437	4.572**	2.646*
	FR	1100	133	0.324	1.177	-1.631	1.133	1.731	1.415
	UK	400	48	-1.261	0.126	1.892	-2.412	3.318**	1.484

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

reject the equality of age and sales distributions for France and the UK. In services, age plays a role in Spain and the UK only, again with the expected sign, while size only matters in Italy and Spain.

Overall, a fair reading of the distributional analysis is that persistent high-growth firms do not seem to differ in any systematic way from high-growth firms.

5 Regression analysis

We next turn to a more standard multivariate regression analysis, 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 discrete indicator

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

according to our classification of growth status observed in the second part of the sample period.

The probability to belong to each category is then modeled as a function of a vector $\mathbf{v}_i$ of explanatory variables

$$P_j := \text{Prob}\left[y_i = j \mid \mathbf{v}_i\right] = F(\beta_j \, \mathbf{v}_i) \ , \tag{4}$$

with $\beta_j, (j = 0, 1, 2)$ the coefficient to be estimated. The vector of explanatory variables includes all the dimensions of firm characteristics and performance: ROA, TFP, IE/S, leverage, age and size (as sales). As we did in the above distributional analysis, all the regressors enter as their average across 2004-2005. Regressors are z-scored, allowing to compare coefficient magnitudes across variables and also across specifications. The lag between growth status (measured in the second time span) and initial firm characteristics (measured in the first time span) reduces potential simultaneity bias.

We estimate a Multinomial Probit model, via full maximum likelihood. This estimation method is a natural choice, 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 estimators.[8]

[8] See Section 8 for a discussion of alternative methods.

Table 6: Multinomial Probit - Main estimates

	Pooled (1)	Italy (2)	Spain (3)	France (4)	UK (5)
Other firms:					
ROA	-0.0260*	-0.0388	-0.0076	-0.0359	-0.0378
	(0.0110)	(0.0222)	(0.0162)	(0.0250)	(0.0346)
IE/S	-0.0289**	0.0008	-0.0427**	-0.0596*	0.0425
	(0.0110)	(0.0239)	(0.0163)	(0.0240)	(0.0324)
LEV	-0.1042***	-0.1803***	-0.0724***	-0.1056***	-0.1023**
	(0.0110)	(0.0209)	(0.0137)	(0.0207)	(0.0363)
log(TFP)	-0.1263***	-0.1551***	-0.1699***	-0.0495	-0.0423
	(0.0150)	(0.0255)	(0.0297)	(0.0290)	(0.0388)
AGE	0.1740***	0.2227***	0.1746***	0.1399***	0.1692***
	(0.0117)	(0.0228)	(0.0193)	(0.0294)	(0.0377)
log(SIZE)	0.1473***	0.2914***	0.1146***	0.0796**	0.0919*
	(0.0146)	(0.0246)	(0.0246)	(0.0282)	(0.0365)
Service dummy	0.0141	0.0146	0.0101	0.0263	0.0105
	(0.0184)	(0.0339)	(0.0347)	(0.0512)	(0.0744)
Country dummies	yes	-	-	-	-
PHG firms:					
ROA	0.0081	0.0097	0.0102	-0.0214	0.0631
	(0.0184)	(0.0385)	(0.0342)	(0.0443)	(0.0466)
IE/S	0.0195	0.0078	0.0350	-0.1260*	0.1186*
	(0.0110)	(0.0329)	(0.0204)	(0.0626)	(0.0514)
LEV	0.0252	0.1121*	-0.0023	0.0074	0.0506
	(0.0151)	(0.0498)	(0.0285)	(0.0262)	(0.0520)
log(TFP)	-0.0260	-0.0395	-0.0387	-0.0391	0.1735*
	(0.0238)	(0.0548)	(0.0404)	(0.0667)	(0.0718)
AGE	-0.0986**	-0.0576	-0.1261	-0.0453	-0.2456
	(0.0354)	(0.0608)	(0.0659)	(0.0765)	(0.1638)
log(SIZE)	-0.1342***	-0.2083***	-0.0831	-0.0792	-0.1104
	(0.0270)	(0.0571)	(0.0584)	(0.0633)	(0.0691)
Service	0.1724***	0.1954**	0.2342***	0.1447	-0.0377
	(0.0449)	(0.0674)	(0.0602)	(0.0971)	(0.1400)
Country dummies	yes	-	-	-	-
Observation	55,454	15,712	24,047	11,152	4,543
Log Pseudo-likelihood	-26,544.17	-7,523.93	-11,549.00	-5,296.98	-2,066.29
Chi-2	1,199.867	646.898	272.015	144.793	113.719

Notes: Coefficient estimates of Multinomial Probit regression from different specifications of model (4), taking High-Growth firms as the baseline category. Explanatory variables in z-scores. Bootstrapped standard errors (100 runs) in parenthesis below the coefficients. Asterisks denote significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Moreover, we don't apply ordered probit or logit models, since these models assume that the observed PHG or HG status of a firm is just the result of a differential reaction to different values of the independent variables, while the underlying mechanism connecting firm characteristics to different growth patterns is the same across HG and PHG firms. Instead, we want to test, and not assume, whether PHG firms can be considered the results of a "stronger" treatment effect.

Despite some computational burden related to the underlying specification of a multivariate Normal distribution, the estimation outcome is simple to interpret as the multiple choice version of a usual binary choice probit, once a baseline category is chosen. In presenting the results, we select the HG firms as the baseline, so that a positive (negative) estimated coefficient capture if the corresponding regressor increases (decreases) the odds of belonging to the group of "other firms" or to the group of PHG firms, with respect to be in the HG group. We report estimated coefficients together with robust standard errors computed via bootstrap. Given the relatively large number of regressors, we avoid to comment 10% significance levels, as they are likely to

Table 7: Multinomial Probit - Manufacturing

	Pooled (1)	Italy (2)	Spain (3)	France (4)	UK (5)
Other firms:					
ROA	-0.0540**	-0.1094***	-0.0086	-0.0184	-0.0251
	(0.0194)	(0.0283)	(0.0281)	(0.0468)	(0.0711)
IE/S	-0.0005	0.0302	-0.0208	-0.0265	0.0400
	(0.0186)	(0.0344)	(0.0344)	(0.0450)	(0.0681)
LEV	-0.1666***	-0.2490***	-0.1206***	-0.1588***	-0.0351
	(0.0166)	(0.0287)	(0.0291)	(0.0419)	(0.0648)
log(TFP)	-0.1737***	-0.1550***	-0.2129***	-0.1700**	-0.1323
	(0.0242)	(0.0362)	(0.0475)	(0.0583)	(0.0766)
AGE	0.1967***	0.2134***	0.2252***	0.2229***	0.0492
	(0.0223)	(0.0324)	(0.0339)	(0.0645)	(0.0641)
log(SIZE)	0.2224***	0.3111***	0.1426**	0.1963***	0.1977**
	(0.0244)	(0.0327)	(0.0438)	(0.0527)	(0.0672)
Country dummies	yes	-	-	-	-
PHG firms:					
ROA	0.0475	0.0246	0.0496	0.0285	0.1132
	(0.0329)	(0.0627)	(0.0587)	(0.1056)	(0.0952)
IE/S	0.0202	0.0323	0.0159	-0.1333	0.0642
	(0.0278)	(0.0674)	(0.0567)	(0.0957)	(0.1432)
LEV	0.0516*	0.1229	-0.0380	0.0726	0.1624
	(0.0256)	(0.0642)	(0.0641)	(0.0665)	(0.1004)
log(TFP)	-0.0573	-0.0206	-0.0452	-0.1266	0.0875
	(0.0545)	(0.0864)	(0.0956)	(0.1595)	(0.1110)
AGE	-0.1199*	-0.0307	-0.3510*	-0.0427	-0.2112
	(0.0593)	(0.0725)	(0.1441)	(0.1514)	(0.2204)
log(SIZE)	-0.2274***	-0.3232***	-0.2001	-0.0587	-0.0381
	(0.0585)	(0.0827)	(0.1233)	(0.1293)	(0.1350)
Country dummies	yes	-	-	-	-
Observations	20,822	8,687	7,537	3,141	1,457
Log Pseudo-likelihood	-9,754.81	-4,069.50	-3,506.94	-1,460.48	-669.87
Chi-2	587.089	401.984	154.803	80.845	25.995

Notes: Coefficient estimates of Multinomial Probit regression from different specifications of model (4), taking High-Growth firms as the baseline category. Explanatory variables in z-scores. Bootstrapped standard errors (100 runs) in parenthesis below the coefficients. Asterisks denote significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

be spurious.[9]

Table 6 shows our main estimates, where we pool together manufacturing and services, and thus regressors also include a dummy for service firms. The top panel report the estimates obtained for the odds of being in the "other firms" category against being an HG firm, while results in the bottom panel show how firm characteristics associate with the odds of being a PHG firm rather than a HG firm.

In Column 1, we pool all the data across countries. The signs and significance of the coefficient obtained for the "other firms" imply that HG firms are more profitable, pay higher interests per unit of sales, have a disproportionately larger debt-to-asset ratio, and are more

[9]Since the variables are in z-scores, the marginal effects at the sample mean of the covariates are proportional to the corresponding coefficients. Standard errors are obtained out of 100 bootstrap runs, which were enough to obtain convergence. We have also applied the usual sandwich-White type of robust standard errors, obtaining the same patterns of statistical significance. The same conclusion holds with respect to all the results presented in the rest of the paper.

efficient. The results complement the univariate distributional analysis, confirming the relevance of leverage, but they also match with the theoretical expectation that profitability and productivity performance do have a discriminatory power. This was not the case in the above distributional comparisons, where we were not controlling for other firm characteristics. Moreover, we still observe a significant role of both age and size, with "other firms" being older and larger than HG firms. Age, in particular, displays the stronger association (coefficient is 0.174), followed by size (0.147). TFP and Leverage have a weaker and similar coefficient (about 0.11, considering the standard errors), while ROA and IE/S play a secondary role, with much smaller coefficients (about 0.02) and weaker statistical significance.

The picture changes completely when we look at the estimated association of regressors with the probability to fall into the PHG category. In this model, indeed, none of the structural firm attributes displays a statistically significant coefficient. The estimates for age and size are negative and significant, matching previous evidence that PHG firms are more likely to be younger and smaller companies than HG firms. Also notice that the service dummy has a positive and significant coefficient, reflecting the fact that the proportion of persistent high-growth firms is larger within services than in manufacturing.

Pooling the data helps increasing the number of observations available for the estimation, especially given the relatively small number of PHG firms. In columns 2-5, we re-estimate the same specification separately for each country. This provides some more flexibility than country dummies in evaluating whether results are invariant to institutional and other country-specific factors. Results fully agree with the picture from the pooled analysis. First, looking at the HG vs "other firms" results, we confirm that leverage and productivity play the major role, together with age and size, in distinguishing HG firms from "other firms". Italy is the country where coefficients are larger for all variables, with size and age having a strong relevance (point estimate about 0.29 and 0.22). Age is the factor with stronger association with being HG in Spain, France and the UK. IE/S is barely significant in Spain and France, while profitability is never significant.

Second, the estimates for the HG/PHG odds confirm the lack of any systematic association between persistence of high-growth performance and all the considered firm characteristics. There are few exceptions, which are however barely significant: IE/S in France and the UK, leverage in Italy, and TFP in the UK. Moreover, age turns out as never statistically significant, while size has a relatively large and significant coefficient only in the case of Italian firms.

In Table 7 and 8 we present a disaggregated analysis distinguishing by manufacturing and services. Results confirm the core evidence. First, in manufacturing, efficiency and financial leverage, together with size and age emerge as the key characteristics distinguishing HG from "other firms", with HG firms generally more efficient, more indebted relatively to own assets, and also smaller and younger. Profitability has a role only in Italy. Yet, PHG firms do not differ systematically from HG firms along any of the included dimensions, with the only exception of size in Italy. Second, the picture is quite similar when we look at services. The main differences with manufacturing are that in services the cost of debt servicing (IE/S) is significantly higher for high-growth firms in most countries (not in the UK), while profitability is never significant in this sector. But we fully confirm that PHG firms do not differ from HG firms under any of the firm attributes. The result is even stronger than in manufacturing, since here even size does not display any statistically significant coefficient.

Our general conclusion is that the drivers of growth predicted by the theory, productivity and leverage in particular, play some role in shaping high-growth patterns, whereas they do not discriminate persistent from sporadic high-growth. Notice that this absence of statistical correlation also downplays the concerns with endogeneity and omitted variables, which, if any, would bias our estimates upward.

Table 8: Multinomial Probit - Services

	Pooled (1)	Italy (2)	Spain (3)	France (4)	UK (5)
Other firms:					
ROA	-0.0068	0.0387	-0.0076	-0.0310	-0.0452
	(0.0140)	(0.0344)	(0.0205)	(0.0281)	(0.0478)
IE/S	-0.0450***	-0.0160	-0.0566***	-0.0708**	0.0317
	(0.0125)	(0.0334)	(0.0170)	(0.0229)	(0.0415)
LEV	-0.0707***	-0.1076***	-0.0511*	-0.0871***	-0.1340**
	(0.0127)	(0.0257)	(0.0199)	(0.0253)	(0.0483)
log(TFP)	-0.1108***	-0.1502***	-0.1583***	-0.0230	0.0059
	(0.0176)	(0.0445)	(0.0304)	(0.0272)	(0.0481)
AGE	0.1614***	0.2325***	0.1552***	0.1131**	0.2411***
	(0.0168)	(0.0388)	(0.0250)	(0.0360)	(0.0596)
log(SIZE)	0.1109***	0.2587***	0.1053***	0.0498	0.0336
	(0.0167)	(0.0421)	(0.0260)	(0.0305)	(0.0428)
Country dummies	yes	-	-	-	-
PHG firms:					
ROA	-0.0016	0.0058	-0.0045	-0.0325	0.0424
	(0.0229)	(0.0473)	(0.0396)	(0.0524)	(0.0527)
IE/S	0.0235	-0.0043	0.0509*	-0.1216	0.1201
	(0.0141)	(0.0458)	(0.0213)	(0.0852)	(0.0736)
LEV	0.0207	0.1030	0.0053	-0.0078	0.0250
	(0.0165)	(0.0618)	(0.0322)	(0.0304)	(0.0741)
log(TFP)	-0.0146	-0.0387	-0.0375	-0.0164	0.2164*
	(0.0294)	(0.0821)	(0.0379)	(0.0776)	(0.0895)
AGE	-0.0901	-0.0713	-0.0978	-0.0495	-0.3023
	(0.0471)	(0.0719)	(0.0762)	(0.0801)	(0.2647)
log(SIZE)	-0.0894*	-0.1224	-0.0500	-0.0780	-0.1503
	(0.0360)	(0.0717)	(0.0494)	(0.0734)	(0.0803)
Country dummies	yes	-	-	-	-
Observations	34,632	7,025	16,510	8,011	3,086
Log Pseudo-likelihood	-16,741.13	-3,436.38	-8,027.73	-3,826.12	-1,388.81
Chi-2	310.385	187.897	168.073	53.093	43.664

Notes: Coefficient estimates of Multinomial Probit regression from different specifications of model (4), taking High-Growth firms as the baseline category. Explanatory variables in z-scores. Bootstrapped standard errors (100 runs) in parenthesis below the coefficients. Asterisks denote significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

6 The role of innovation

The recent empirical literature on high-growth firms suggests that innovativeness might represent a distinguishing feature of this type of firms. High-growth firms tend to be more concentrated in high-tech sectors or in sectors closer to the technological frontier, and they also tend to be more involved than other firms into R&D and patenting activity. There is no direct evidence, however, about the innovation patters of persistent high-growth firms. In this section we replicate our regression analysis including among the regressors the value of intangible assets (INTASS) as a firm-level proxy for innovativeness.[10]

In Table 9 we show the results of the specification pooling data across manufacturing and services. Point estimates and patterns of statistical significance for the economic and financial

[10]The Amadeus data are known to lack information about R&D expenditures, while information on patenting activity is available only for very few firms. Intangible assets have instead a good coverage and represent a suitable alternative proxy, repeatedly adopted in innovation studies, since, e.g., Hall (1999).

Table 9: Intangible assets - Multinomial Probit, main estimates

	Pooled (1)	Italy (2)	Spain (3)	France (4)	UK (5)
Other firms:					
ROA	-0.0291**	-0.0492*	-0.0081	-0.0379	-0.0388
	(0.0105)	(0.0218)	(0.0170)	(0.0229)	(0.0378)
IE/S	-0.0235*	0.0102	-0.0412*	-0.0533**	0.0584
	(0.0096)	(0.0236)	(0.0163)	(0.0205)	(0.0419)
LEV	-0.1056***	-0.1836***	-0.0719***	-0.1120***	-0.1073***
	(0.0103)	(0.0225)	(0.0159)	(0.0235)	(0.0320)
log(TFP)	-0.1257***	-0.1534***	-0.1694***	-0.0519	-0.0443
	(0.0151)	(0.0271)	(0.0274)	(0.0291)	(0.0390)
AGE	0.1700***	0.2093***	0.1743***	0.1376***	0.1551***
	(0.0122)	(0.0245)	(0.0248)	(0.0308)	(0.0390)
log(SIZE)	0.1699***	0.3371***	0.1203***	0.1003**	0.1500***
	(0.0151)	(0.0290)	(0.0255)	(0.0321)	(0.0414)
log(INTASS)	-0.0454***	-0.0857***	-0.0120	-0.0434	-0.1135**
	(0.0121)	(0.0210)	(0.0170)	(0.0238)	(0.0382)
Service dummy	0.0140	0.0137	0.0101	0.0255	0.0096
	(0.0195)	(0.0384)	(0.0281)	(0.0432)	(0.0675)
Country dummies	yes	-	-	-	-
PHG firms:					
ROA	0.0053	0.0120	0.0065	-0.0244	0.0623
	(0.0170)	(0.0419)	(0.0300)	(0.0463)	(0.0466)
IE/S	0.0235*	0.0079	0.0388*	-0.1061	0.1252*
	(0.0111)	(0.0357)	(0.0198)	(0.0621)	(0.0615)
LEV	0.0238	0.1141*	-0.0007	-0.0041	0.0493
	(0.0134)	(0.0454)	(0.0292)	(0.0266)	(0.0550)
log(TFP)	-0.0256	-0.0376	-0.0353	-0.0434	0.1744**
	(0.0223)	(0.0563)	(0.0361)	(0.0539)	(0.0637)
AGE	-0.1026**	-0.0534	-0.1313	-0.0479	-0.2424
	(0.0322)	(0.0529)	(0.0775)	(0.0894)	(0.1590)
log(SIZE)	0.1147***	-0.2148***	-0.0580	-0.0407	-0.0960
	(0.0251)	(0.0482)	(0.0512)	(0.0576)	(0.0788)
log(INTASS)	-0.0409	0.0173	-0.0624	-0.0865	-0.0243
	(0.0237)	(0.0430)	(0.0386)	(0.0501)	(0.0736)
Service dummy	0.1722***	0.1957**	0.2356**	0.1402	-0.0340
	(0.0441)	(0.0712)	(0.0769)	(0.0904)	(0.1527)
Country dummies	yes	-	-	-	-
Observations	55,454	15,712	24,047	11,152	4,543
Log Pseudo-likelihood	-26,534.74	-7,514.24	-11,547.47	-5,294.18	-2,061.79
Chi-2	1,121.293	762.728	264.793	114.849	90.821

Notes: Coefficient estimates of Multinomial Probit regression from different specifications of model (4), taking High-Growth firms as the baseline category. Explanatory variables in z-scores. Bootstrapped standard errors (100 runs) in parenthesis below the coefficients. Asterisks denote significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

variables are substantially identical to the main results presented in the previous Section. The picture is basically unchanged also concerning size and age, although adding intangibles affect the estimated coefficient of these two latter variables. Intangibles present themselves a negative and significant coefficient in the odds of being "other" vs HG firms, at least in some cases (pooled analysis, and in Italy and the UK), in accordance with the evidence that high-growth firms tend to be more innovative. However, intangibles do not have any statistically significant discriminatory power in distinguishing persistent high-growth performers from "simple" high growers.

We find consistent results also when distinguishing manufacturing and services, in Table 10 and Table 11. Once again, structural and demographic variables can discriminate between HG and other firms, but they have limited role in distinguishing persistent high-growth firms. The only noticeable difference with respect to the aggregate analysis is in services, where intangible

Table 10: Intangible assets - Multinomial Probit, Manufacturing

	Pooled (1)	Italy (2)	Spain (3)	France (4)	UK (5)
Other firms:					
ROA	-0.0569**	-0.1149***	-0.0087	-0.0207	-0.0263
	(0.0192)	(0.0336)	(0.0329)	(0.0474)	(0.0596)
IE/S	0.0039	0.0381	-0.0205	-0.0162	0.0590
	(0.0193)	(0.0354)	(0.0409)	(0.0394)	(0.0768)
LEV	-0.1664***	-0.2487***	-0.1204***	-0.1673***	-0.0406
	(0.0165)	(0.0295)	(0.0331)	(0.0474)	(0.0635)
log(TFP)	-0.1699***	-0.1489***	-0.2127***	-0.1701**	-0.1264
	(0.0244)	(0.0389)	(0.0424)	(0.0655)	(0.0813)
AGE	0.1929***	0.2054***	0.2251***	0.2175**	0.0394
	(0.0224)	(0.0287)	(0.0460)	(0.0691)	(0.0615)
log(SIZE)	0.2400***	0.3350***	0.1438**	0.2289***	0.2349***
	(0.0259)	(0.0354)	(0.0458)	(0.0689)	(0.0674)
log(INTASS)	-0.0372	-0.0497	-0.0025	-0.0693	-0.0836
	(0.0218)	(0.0328)	(0.0322)	(0.0457)	(0.0672)
Country dummies	yes	-	-	-	-
PHG firms:					
ROA	0.0492	0.0272	0.0446	0.0313	0.1128
	(0.0325)	(0.0561)	(0.0661)	(0.0892)	(0.0997)
IE/S	0.0211	0.0360	0.0188	-0.1744	0.0547
	(0.0315)	(0.0693)	(0.0584)	(0.1083)	(0.1587)
LEV	0.0523*	0.1220	-0.0348	0.0917	0.1594
	(0.0250)	(0.0711)	(0.0584)	(0.0732)	(0.0984)
log(TFP)	-0.0582	-0.0224	-0.0388	-0.1282	0.0805
	(0.0552)	(0.0842)	(0.1005)	(0.1373)	(0.1132)
AGE	-0.1167	-0.0278	-0.3561*	-0.0351	-0.2049
	(0.0600)	(0.0687)	(0.1568)	(0.1679)	(0.2212)
log(SIZE)	-0.2342***	-0.3304***	-0.1735	-0.1249	-0.0551
	(0.0640)	(0.0863)	(0.1185)	(0.1431)	(0.1323)
log(INTASS)	0.0185	0.0221	-0.0641	0.1476	0.0447
	(0.0497)	(0.0648)	(0.0697)	(0.1088)	(0.1387)
Country dummies	yes	-	-	-	-
Observations	20,822	8,687	7,537	3,141	1,457
Log Pseudo-likelihood	-9,752.11	-4,067.63	-3,506.58	-1,457.33	-668.84
Chi-2	666.365	451.100	143.440	104.552	25.179

Notes: Coefficient estimates of Multinomial Probit regression from different specifications of model (4), taking High-Growth firms as the baseline category. Explanatory variables in z-scores. Bootstrapped standard errors (100 runs) in parenthesis below the coefficients. Asterisks denote significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 11: Intangible assets - Multinomial Probit, Services

	Pooled	Italy	Spain	France	UK
	(1)	(2)	(3)	(4)	(5)
Other firms:					
ROA	-0.0099	0.0224	-0.0083	-0.0327	-0.0455
	(0.0158)	(0.0288)	(0.0214)	(0.0269)	(0.0398)
IE/S	-0.0388**	-0.0009	-0.0547**	-0.0662**	0.0444
	(0.0119)	(0.0360)	(0.0177)	(0.0214)	(0.0443)
LEV	-0.0730***	-0.1194***	-0.0505*	-0.0919***	-0.1396*
	(0.0138)	(0.0278)	(0.0206)	(0.0274)	(0.0543)
log(TFP)	-0.1123***	-0.1605***	-0.1580***	-0.0254	-0.0015
	(0.0184)	(0.0437)	(0.0348)	(0.0331)	(0.0437)
AGE	0.1576***	0.2133***	0.1546***	0.1118***	0.2242***
	(0.0165)	(0.0352)	(0.0281)	(0.0302)	(0.0529)
log(SIZE)	0.1345***	0.3291***	0.1123***	0.0646	0.0993*
	(0.0209)	(0.0467)	(0.0286)	(0.0340)	(0.0489)
log(INTASS)	-0.0471***	-0.1195***	-0.0151	-0.0308	-0.1201*
	(0.0137)	(0.0317)	(0.0214)	(0.0268)	(0.0477)
Country dummies	yes	-	-	-	-
PHG firms:					
ROA	-0.0062	0.0076	-0.0079	-0.0391	0.0421
	(0.0234)	(0.0509)	(0.0414)	(0.0520)	(0.0704)
IE/S	0.0299	-0.0040	0.0553*	-0.0815	0.1273
	(0.0162)	(0.0497)	(0.0232)	(0.0740)	(0.0793)
LEV	0.0172	0.1052	0.0067	-0.0307	0.0241
	(0.0187)	(0.0695)	(0.0347)	(0.0346)	(0.0792)
log(TFP)	-0.0164	-0.0375	-0.0354	-0.0274	0.2147*
	(0.0315)	(0.0825)	(0.0436)	(0.0674)	(0.0894)
AGE	-0.0968*	-0.0664	-0.1030	-0.0517	-0.3012
	(0.0459)	(0.0819)	(0.0735)	(0.0937)	(0.2920)
log(SIZE)	-0.0584	-0.1230	-0.0256	-0.0105	-0.1238
	(0.0313)	(0.0864)	(0.0534)	(0.0678)	(0.0970)
log(INTASS)	-0.0667*	0.0069	-0.0603	-0.1579**	-0.0453
	(0.0267)	(0.0639)	(0.0447)	(0.0611)	(0.1064)
Country dummies	yes	-	-	-	-
Observations	34,632	7,025	16,510	8,011	3,086
Log Pseudo-likelihood	-16,733.67	-3,428.25	-8,026.59	-3,821.87	-1,385.56
Chi-2	437.888	200.566	176.130	70.426	57.515

Notes: Coefficient estimates of Multinomial Probit regression from different specifications of model (4), taking High-Growth firms as the baseline category. Explanatory variables in z-scores. Bootstrapped standard errors (100 runs) in parenthesis below the coefficients. Asterisks denote significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 12: Distributional comparison by Age and Size - Manufacturing

	Country	#HG	#PHG	ROA	IE/S	LEV	log(TFP)
Young	Pooled	626	87	0.948	0.613	-1.381	0.713
	IT	223	39	1.031	0.796	-1.277	3.235*
	ES	288	33	0.074	-0.423	-0.113	0.070
	FR	91	12	-0.401	1.917	-2.166	0.438
	UK	24	3	0.520	-0.233	-0.605	0.442
Middle/Old	Pooled	2430	189	-2.059	-3.324**	0.857	1.726
	IT	1052	99	1.726	-2.532	-2.661*	3.205*
	ES	854	39	0.121	-0.693	-1.168	2.380
	FR	358	30	0.128	-0.602	-1.068	0.538
	UK	166	21	-1.015	-0.832	-2.856*	-0.699
Micro-Small	Pooled	2355	239	1.815	-1.391	-3.295**	0.019
	IT	906	126	2.316	-1.558	-2.454	3.377**
	ES	1042	71	-0.057	-0.967	-1.715	1.454
	FR	364	36	-0.148	0.220	-2.095	0.752
	UK	43	6	-1.928	0.395	-0.673	-0.995
Medium-Large	Pooled	701	37	-1.173	-0.320	-2.105	1.602
	IT	369	12	-1.416	-0.572	-1.182	0.688
	ES	100	1	-	-	-	-
	FR	85	6	-0.384	0.075	-0.232	-0.138
	UK	147	18	0.478	-1.247	-3.025*	-0.109

Notes: Fligner-Policello (FP) test of stochastic equality. Young firms are ≤ 5 years old in 2004. Micro-Small firms defined as firms with < 50 employees in 2004. HG firms as benchmark within each class: a positive and significant FP statistic means that HG firms dominates. Asterisks denote significance levels: * $p < 0.01$, ** $p < 0.001$.

assets are found to increase the probability to be in the HG group (in Italy and in the UK) or in the PHG category (in France), but at very low levels of statistical significance.[11]

Overall, we confirm our key finding that firms who display a subsequent pattern of persistent high-growth performance are neither more productive, nor more profitable, nor characterized by peculiar financial conditions in the initial years.

7 Size and age

The statistical exercises presented so far provide mixed results on the role of age and size, and in particular concerning the discriminatory power of such demographic characteristics across HG and PHG firms. Despite there is some variation across sectors and countries, distributional comparisons suggest that PHG firms tend to be smaller and younger than HG firms, especially in manufacturing. On the contrary, in the Multinomial Probit regressions we do not find systematic evidence that persistent high-growth firms differ from high-growth firms in terms of age and size.

Motivated by the emphasis given to age and size in the literature, we propose a further look at the role of these firm attributes. We want to explore whether age and size interplay with our negative result about the lacking association between persistence of high-growth and economic

[11] As an alternative way to explore the role of innovation, we have also estimated our baseline Multinomial Probit augmented with dummy indicators identifying groups of sectors by their innovative characteristics. For manufacturing, we have experimented with dummies for Low vs. High-Tech industries (EUROSTAT classification) and distinguishing the four classical Pavitt (1984) taxonomy classes. For services, we distinguished KISS vs. non-KISS sectors (EUROSTAT taxonomy). The results about the main structural and demographic characteristics replicate our main conclusions. Moreover, sectoral dummies turn out as statistically significant only in some specific cases, and thus provide a weak contribution to predict persistence of high-growth status.

Table 13: Distributional comparison by Age and Size - Services

	Country	#HG	#PHG	ROA	IE/S	LEV	log(TFP)
Young	Pooled	1333	218	-1.971	0.795	0.600	-2.589*
	IT	225	47	-0.263	-0.702	-0.977	1.120
	ES	743	105	-2.049	0.891	2.040	-1.314
	FR	268	43	-0.907	2.368	-1.335	-1.241
	UK	97	23	-0.535	-1.362	-0.308	-0.331
Middle/Old	Pooled	3621	348	2.778*	-1.501	-3.113*	1.065
	IT	778	97	2.121	-1.008	-1.687	1.893
	ES	1708	136	2.132	-2.865*	-2.509	2.224
	FR	832	90	1.262	-0.034	-0.808	2.182
	UK	303	25	-1.455	2.433	-1.511	-3.649**
Micro-Small	Pooled	4210	505	0.882	-0.495	-3.148*	-0.535
	IT	811	122	1.064	-0.537	-2.339	2.157
	ES	2298	235	-0.304	-1.424	-1.438	0.891
	FR	966	126	0.731	1.293	-2.098	0.606
	UK	135	22	0.341	-0.346	-1.918	-1.974
Medium-Large	Pooled	744	61	-0.073	-1.274	-1.049	-0.633
	IT	192	22	1.632	-1.922	-0.333	1.052
	ES	153	6	2.823*	-0.208	-4.805**	0.965
	FR	134	7	-0.750	-0.273	1.285	1.518
	UK	265	26	-2.152	0.159	-0.659	-1.805

Notes: Fligner-Policello (FP) test of stochastic equality. Young firms are ≤ 5 years old in 2004. Micro-Small firms defined as firms with < 50 employees in 2004. HG firms as benchmark within each class: a positive and significant FP statistic means HG firms dominates. Asterisks denote significance levels: * $p < 0.01$, ** $p < 0.001$.

or financial attributes. That is, it may be the case that although efficiency, profitability and financial indicators *on average* cannot discriminate between HG and PHG firms, the association of the same variables with PHG status vary across firms of different size and age. We therefore propose a further exercise dividing the firms into age and size classes, and then, within each size and age class, repeat the Fligner-Policello test of stochastic dominance to compare the empirical distribution of productivity, profitability and financial indicators across HG and PHG firms.[12] To have a reasonable number of observations in each class, we build two size classes based on employment exploiting the standard EUROSTAT distinction between Micro-Small (< 50 employees) and Medium-Large (≥ 50 employees) firms, and we define Young firms as those with age ≤ 5, to be compared against Medium-Old-aged firms with age ≥ 6 years. The assignment to the different classes is defined according to age and size in the first year of the sample.

We focus on results breaking down by countries and sector of activity. The general finding is that the null of equality of distributions can be rejected only in few particular cases, and generally at low levels of significance. In manufacturing (see Table 12), we find that young HG firms outperform young PHG firms in terms of TFP in Italy, whereas mid-old HG firms are more productive, but less leveraged than mid-old PHG firms in the same country. Higher leverage also characterize mid-old PHG firms in the UK. A similar ranking in productivity in Italy also holds if we look at size, with micro-small HG firms more productive than micro-small PHG firms. And leverage also plays a role in the UK, where we see that medium-large PHG firms are more indebted than HG firms in the same age class.

Concerning services (in Table 13), the evidence is of an even weaker statistical difference across PHG and HG firms. Within young firms the null of distributional equality is basically never rejected, whereas within mid-old firms only TFP seems to play some more strongly

[12] Regression analysis within each class is prevented by the small number of PHG firms falling into each class, especially when breaking down the analysis by countries and sectors.

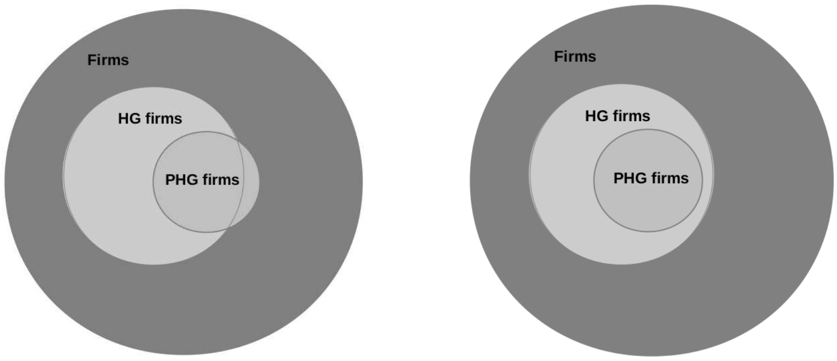

Figure 2: Definition of HG, PHG and other firms. Left panel: PHG is not a subset of HG. Right panel: PHG is a subset of HG

statistically significant role, but only in the UK, with PHG more productive than HG firms. Disaggregating by size only adds that medium-large PHG firms are significantly more leveraged than medium-large HG firms in Spain.

Once again, we corroborate our main conclusion that the set of economic and financial characteristics does not provide any robust discriminatory power in distinguishing firms experiencing persistent high-growth performance.

8 Alternative regression models

Our identification strategy of HG and PHG firms makes standard panel regression models not viable. In principle, with the data at hand, one could implement a panel regression approach with the HG annual growth rate as the dependent variable. This would basically correspond to a modification of the usual augmented Gibrat model, limiting the scope of the analysis to a very specific notion of persistence based on the simple autocorrelation structure of the growth rates. We thus decided not to pursue that approach (and a large literature already did, as discussed in Section 2).

Further notice that the two categories of HG and PHG firms, as we define them, are not nested. In fact, a company can be a PHG firm without falling at the same time in the HG group (see left plot in Figure 2). This is the case, for instance, of a firm displaying a powerful growth record in four out of the final five years of the sample, but next having such a poor performance in the remaining year that the firm is outside the top decile of the annualized average growth rate distribution. The Multinomial Probit is theoretically superior in this situation. However, since only a quite small number of PHG firms are not HG firms in the data (76 firms in total), we provide a robustness check estimating an alternative econometric specification where we impose that PHG firms are a subset of the HG category (c.f. the right panel in Figure 2), as if the decision to be PHG is nested into or dependent from the decision to be HG.

Such structure, implying that a firm can be PHG only conditional upon being HG, naturally leads to a two-step conditional probit. In practice, we modify the definition of growth status by assigning to the "other firms" group all the firms which are PHG, but not HG. Next, we estimate a first probit model for the probability to be selected in the HG set (which now includes the PHG set)

$$P^1 := \text{Prob}\left[y_i \in \{1,2\} \,|\, \mathbf{v}_i\right] = F(\beta^1 \, \mathbf{v}_i) \;, \tag{5}$$

and then a second-step probit on the probability to be selected in the PHG set, conditional on being in the HG set

Table 14: Conditional Probit

	Pooled (1)	Italy (2)	Spain (3)	France (4)	UK (5)
First step probit: dep. variable is Prob(HG=1)					
ROA	0.0198**	0.0305*	0.0059	0.0233	0.0376
	(0.0075)	(0.0145)	(0.0115)	(0.0174)	(0.0238)
IE/S	0.0243***	0.0006	0.0363**	0.0378*	-0.0035
	(0.0062)	(0.0142)	(0.0120)	(0.0157)	(0.0256)
LEV	0.0786***	0.1395***	0.0530***	0.0783***	0.0793**
	(0.0074)	(0.0159)	(0.0111)	(0.0161)	(0.0249)
log(TFP)	0.0899***	0.1104***	0.1202***	0.0327	0.0437
	(0.0103)	(0.0207)	(0.0189)	(0.0220)	(0.0245)
AGE	-0.1322***	-0.1678***	-0.1335***	-0.1035***	-0.1371***
	(0.0094)	(0.0167)	(0.0142)	(0.0207)	(0.0299)
log(SIZE)	-0.1160***	-0.2315***	-0.0852***	-0.0639**	-0.0764**
	(0.0111)	(0.0202)	(0.0169)	(0.0213)	(0.0246)
Service dummy	-0.0005	-0.0015	0.0035	-0.0043	-0.0121
	(0.0147)	(0.0211)	(0.0202)	(0.0356)	(0.0496)
Country dummies	yes	-	-	-	-
Observations	55,454	15,712	24,047	11,152	4,543
Log Pseudo-likelihood	-23,731.62	-6,637.67	-10,438.27	-4,718.40	-1,850.92
Chi-2	632.493	445.340	290.036	76.821	51.610
Second step probit: dep. variable is Prob(PHG=1)					
ROA	0.0208	0.0346	0.0149	-0.0028	0.0899
	(0.0173)	(0.0369)	(0.0308)	(0.0462)	(0.0577)
IE/S	0.0346**	0.0161	0.0556**	-0.0929	0.1289
	(0.0126)	(0.0316)	(0.0179)	(0.0624)	(0.0701)
LEV	0.0528**	0.1315**	0.0283	0.0392	0.0615
	(0.0198)	(0.0474)	(0.0266)	(0.0372)	(0.0946)
log(TFP)	-0.0115	-0.0218	-0.0229	-0.0376	0.1725**
	(0.0239)	(0.0406)	(0.0361)	(0.0503)	(0.0643)
AGE	-0.1093***	-0.0785*	-0.1509**	-0.0385	-0.2306
	(0.0286)	(0.0392)	(0.0543)	(0.0528)	(0.1304)
log(SIZE)	-0.1215***	-0.2356***	-0.0486	-0.0819	-0.1099
	(0.0274)	(0.0408)	(0.0370)	(0.0530)	(0.0817)
Service dummy	0.1546***	0.1678*	0.2013**	0.1816	-0.0727
	(0.0392)	(0.0731)	(0.0654)	(0.1071)	(0.1711)
Country dummies	yes	-	-	-	-
Observations	8,776	2,530	3,874	1,711	661
Log Pseudo-likelihood	-2,526.40	-777.98	-983.43	-528.37	-212.60
Chi-2	175.799	92.236	47.739	10.963	21.515

Notes: Explanatory variables in z-scores. Bootstrapped standard errors (100 runs) in parenthesis below the coefficients. Asterisks denote significance levels: $^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$.

$$P^2 := \text{Prob}\left[y_i = 2 \,|\, y_i \in \{1,2\}, \mathbf{v}_i\right] = F(\beta^2\, \mathbf{v}_i)\ . \tag{6}$$

This two-step model assumes that the idiosyncratic term in the second conditional regression is independent from the error term in the first step regression. In this sense it represents the restriction of the multinomial probit to a degenerate error variance-covariance matrix.[13]

In Table 14 we show results for the specifications pooling the data across manufacturing and services. The patterns of statistical significance exactly match with the estimates from the corresponding Multinomial Probit models reported in Table 6 above. The point estimates are also quite similar, providing a similar conclusion about the relatively weak power of economic and financial factors in predicting persistence in high-growth performance. We therefore conclude that our findings are robust to the alternative estimation method.[14]

[13] As in the Multinomial Probit specifications, the regressors include the averages of the firm attributes over computed over 2004-2005, in z-scores, and we report standard errors computed over 100 bootstrap runs.

[14] In unreported estimates we have repeated the two-step conditional probit for all the other specifications

9 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 to find a significant association between efficiency, profitability and financial conditions, on the one hand, and the ability of firms to succeed in achieving high-growth records, 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, Spanish and UK 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, more common among small and young firms, but we lack of attempts to investigate the more structural economic and financial determinants of persistent high-growth.

Our findings provide a negative result. We do find some support that economic and financial characteristics (efficiency and TFP in particular) are associated with high-growth. However, none of the supposedly key drivers of growth systematically stand out as significant predictors of persistently high-growth performance. The result is robust across countries, it does not change across manufacturing and services, and it also holds within groups of firms of different age and size. Moreover, we also find that firm innovativeness (as proxied by intangible assets) is not able to discriminate persistent high-growth from simple high-growth, and that firm size and age do not play a systematic role, although persistently high-growers are younger and smaller in some countries.

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. An interesting extension of the analysis would be to include factors of more direct derivation from management research, for which we do not have data, e.g. looking deeper into organizational characteristics, or exploring the role of differences in the underlying firm strategies and managerial or entrepreneurial characteristics. And one cannot rule out, at least in principle, that persistent high-growth primarily occurs at random, guided by "mere luck", so that it would 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, with all their limitations, our findings represent a challenge for the theory and also raise concerns about the longer run effectiveness of existing policies targeting high-growth companies. The lacking association between efficiency and persistence in high-growth performance, in particular, suggests that supporting high-growth firms could have no impact on the overall competitiveness of sectors and countries.

presented in the previous sections. Results are in accordance with the Multinomial Probit analysis.

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Appendix

Table 15: Number of firms by country and sector - Manufacturing

NACE	IT	ES	FR	UK
10	724 (688)	927 (906)	415 (399)	140 (77)
11	143 (140)	173 (163)	58 (57)	38 (18)
12	2 (0)	2 (0)	0 (0)	2 (1)
13	507 (485)	310 (306)	68 (63)	28 (15)
14	280 (265)	179 (177)	41 (39)	15 (10)
15	268 (258)	206 (204)	31 (30)	1 (1)
16	176 (169)	386 (385)	186 (182)	23 (15)
17	249 (233)	135 (129)	57 (52)	46 (30)
18	145 (140)	506 (506)	187 (185)	64 (49)
19	38 (35)	7 (6)	5 (5)	8 (7)
20	447 (421)	265 (257)	112 (95)	116 (70)
21	114 (89)	29 (17)	22 (14)	34 (17)
22	553 (532)	350 (344)	196 (183)	70 (43)
23	459 (440)	516 (505)	169 (159)	47 (30)
24	363 (337)	194 (187)	37 (34)	34 (24)
25	1422 (1386)	1511 (1504)	615 (595)	166 (127)
26	279 (261)	92 (84)	111 (98)	88 (64)
27	404 (381)	160 (154)	69 (57)	55 (32)
28	1231 (1178)	442 (436)	202 (191)	139 (93)
29	173 (149)	162 (142)	69 (65)	44 (20)
30	88 (81)	28 (27)	27 (23)	28 (11)
31	310 (306)	425 (423)	80 (79)	31 (19)
32	197 (193)	169 (167)	94 (92)	184 (136)
33	115 (111)	363 (363)	290 (284)	56 (41)
Total	8687 (8278)	7537 (7392)	3141 (2981)	1457 (950)

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

Table 16: Number of firms by country and sector - Service

NACE	IT	ES	FR	UK
45	773 (770)	1596 (1592)	1115 (1110)	337 (234)
46	2949 (2887)	5092 (5048)	2122 (2074)	555 (429)
47	782 (721)	3627 (3604)	1753 (1732)	202 (100)
49	320 (293)	992 (978)	466 (448)	147 (75)
50	22 (21)	32 (32)	6 (6)	15 (8)
51	11 (10)	5 (2)	1 (1)	24 (12)
52	292 (265)	252 (247)	94 (81)	74 (42)
53	4 (3)	22 (22)	3 (3)	5 (2)
55	162 (156)	443 (436)	312 (311)	112 (80)
56	105 (92)	1171 (1162)	456 (447)	73 (29)
58	84 (75)	137 (130)	83 (75)	61 (28)
59	16 (15)	43 (43)	31 (30)	21 (14)
60	22 (22)	29 (27)	6 (4)	7 (3)
61	18 (17)	68 (61)	16 (15)	42 (26)
62	184 (172)	237 (230)	119 (103)	135 (111)
63	72 (68)	15 (15)	20 (18)	15 (13)
64	41 (26)	33 (12)	71 (42)	157 (101)
66	17 (15)	40 (39)	8 (6)	29 (25)
68	160 (148)	218 (217)	75 (75)	61 (44)
69	70 (66)	298 (294)	57 (57)	11 (9)
70	155 (127)	125 (114)	89 (39)	282 (106)
71	99 (91)	271 (262)	150 (139)	46 (28)
72	23 (22)	20 (18)	16 (14)	15 (8)
73	85 (83)	202 (202)	68 (66)	39 (31)
74	51 (50)	188 (187)	34 (34)	44 (33)
75	0 (0)	29 (29)	1 (1)	1 (1)
77	43 (41)	174 (171)	82 (77)	81 (60)
78	10 (8)	8 (6)	7 (4)	55 (35)
79	64 (62)	117 (112)	10 (10)	32 (22)
80	37 (31)	49 (45)	15 (14)	10 (5)
81	82 (58)	234 (215)	204 (191)	26 (9)
82	91 (86)	86 (82)	78 (75)	199 (128)
90	15 (13)	40 (40)	24 (24)	9 (5)
91	6 (2)	6 (6)	11 (11)	1 (1)
92	6 (5)	87 (84)	39 (38)	10 (2)
93	74 (73)	176 (175)	52 (51)	40 (30)
94	0 (0)	6 (6)	0 (0)	8 (7)
95	28 (27)	103 (103)	35 (34)	3 (1)
96	52 (48)	239 (236)	282 (281)	102 (68)
Total	7025 (6669)	16510 (16284)	8011 (7741)	3086 (1965)

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