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

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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 age, size and innovation activity.

JEL codes: D22, D24, L26

Keywords: High-growth firms, Persistent high-growth, Productivity, Firm age, Firm 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; Kenney and Patton, 2013). On the one hand, managers and consultants try to identify 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 both macro-economic or institutional factors, external to the firm, and to micro-economic characteristics specific to a given firm. The latter often include demographic variables such as age and size, together with more economic determinants such as 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. The debate is ongoing, with recent evidence showing that young age (rather than small size) may be the main contributors to growth and employment, at least in the US (Haltiwanger et al., 2013). The implication has been to confirm and expand policies that foster creation of new firms, in the hope that they sustain the overall economy.

In this paper we offer a different perspective. Instead of searching for the possible determinants of high-growth, we want to identify the factors that make a firm a *persistent* high-growing firm. The motivation of this shift of focus rests in the consideration that, while high-growth firms are surely a key ingredient of modern economies, 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. The ability to repeatedly outperform in terms of growth constitutes indeed the kind of behavior that is likely connected with the presence of structural comparative advantages and exceptional capabilities inside the firm. Firms like PayPall or Amazon, which are mentioned by the qualitative literature on the subject as outstanding examples of gazelles, did in fact not only display an extraordinary initial growth record, but they also achieved an exceptional pattern of persistent growth in revenues across several years. This is in fact uncommon, as the dynamics underlying a fast expansion can vary, even in substantial form, from company to company: 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 (Delmar et al., 2003).

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 even cast doubts on the very existence of persistence in high-growth (Daunfeldt and Halvarsson, 2015). More generally, even if some degree of persistence in high-growth is identified, the search of explanatory causes is limited to the exploration of mere demographic characteristics of the firm, such as size, age or sector of activity. In this study we try to extend this range of analysis to include measures of superior operating capability. 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. One wants indeed 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 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 panels of Italian, French, Spanish and UK incumbents, we identify two groups of high-growth and persistent high-growth firms. It turns out that only a small proportion of firms is able to sustain superior growth performance over time. We then analyze how productivity, profitability and financial performances exhibited by different firms in the initial years of the sample relate with the patterns of high-growth and persistent high-growth in the subsequent years. We perform both non-parametric and parametric analyses. First, we investigate whether high-growers, persistently high-growers and other firms display distributional differences along the set of the key variables taken to proxy for the operational performance and the financial status of firms. Second, we turn to discrete choice models 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 their 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, where we include control for sector and firm-level innovativeness, disaggregate the analysis by size and age classes, and apply alternative estimation methods.

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 scarce 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. Garsaa and Levratto (2015) show that high-growth firms benefit more than other firms from tax-rebates reducing non-wage components of cost of labour in French manufacturing.

The empirical investigation of the micro-level determinants of high-growth is more recent (see Audretsch et al., 2014, for a recent review). Part of the debate centers around whether size or age do constitute the key characteristics of high-growing, and thus job-creating, firms. Most studies conclude that high-growth is indeed more frequent among small and young companies, although a recent influential paper by Haltiwanger et al. (2013) on US data finds that young age is far more important for employment growth than small size. Beyond those more demographic characteristics, however, existing studies have somewhat disproportionately focused only 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, and finds 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. And research has just started (Coad et al., 2015) to investigate the mediating role of age in the links between innovation (as R&D) and high-growth.

Concerning the identification and measure of persistence in the growth dynamics of firms, traditional studies, complying with the Gibrat's Law literature, look at the persistence of the "average firm" growth rate, usually by estimating the autocorrelation structure in the growth process within a sector or a sample of firms. The results are mixed, ranging from the view that growth is indeed a random walk advanced in Geroski (2002), to the evidence of long-lasting autocorrelation (up to the 7^{th} lag) found in Bottazzi et al. (2001).[1] More recent empirical research considers the degree of persistence in the top-tail of the growth rates distribution, by means of quantile autoregression or transition probability matrices. Evidence is still inconclusive about the very existence of persistent high-growers. Hölzl (2014) show that most of high-growth firms do not replicate their high-growth performance over time, and Daunfeldt and Halvarsson (2015) document that high-growth firms are basically "one-hit wonders", since in fact firms experiencing strong job losses in one period are most likely to become high-growth units in the next

[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.

period. 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 achieve smoother dynamics. Conversely, Capasso et al. (2013) conclude that persistent outperformers are more often present among micro firms.

Overall, to the best of our knowledge, no attempts have been made to address if more structural, economic or financial, factors are distinguishing features of persistent high-growth companies. This is the key contribution we seek to offer in this article.

In doing so we exploit the available panel data structure to provide definitions of high-growth and persistent high-growth firms that go beyond the usual notion of autocorrelation. Indeed, as the influential contributions by Delmar et al. (2003) and Delmar (2006) have highlighted, high-growth firms do not all grow in the same way. Observed patterns differ by demographic characteristics such as size, industry affiliation or firm age, and by type of governance. Differences are sharp, ranging from cases of "super absolute growers", which are typically small- and medium-sized firms operating in knowledge intensive manufacturing industries, to the case of "erratic one-shot growers", which are more common among small-sized firms in low-technology service sectors. Results in Hölzl (2014) already witness that the degree of persistence in high-growth might depend upon the criterion adopted for the identification of high-growth companies. This motivates us to adopt a multidimensional definition involving both sales and employment growth, and to embark into a series of robustness checks with respect to possibly alternatives definitions of what high-growth means.

In search for a guiding framework for our empirical analysis, we refer to what existing theories of firm-industry dynamics suggest as potential drivers of high-growth and persistence of high-growth.

We primarily draw from modern heterogeneous firms models, 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 the arrival of a cohort of entrants with their idiosyncratic initial endowment, as the first driver. The shock or the initial endowment regard 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.

The models do not directly discuss the emergence of high-growth firms, but 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 efficiency and profits should reflect 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 about their ultimate effect. On the one hand, the availability of internal resources (cash flow) and the relative ability to stand on own resources rather than on debts, can ease the need for and the dependence from external credit. On the other hand, sounder financial conditions also warrant to potential investors a superior capability to meet debt servicing, thus eventually resulting into easier access to further credit and into 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 (Bottazzi et al., 2014).

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. It seems possible to derive a general principle according to which firms that are able to persistently keep their comparative advantages in terms of efficiency and profit, should also be more likely to witness a higher growth over time. However, some scholars have even advanced the hypothesis that randomness (or "mere luck") is the most appropriate account of firms' persistent success (Barney, 1997).[2]

3 Identification of high-growth and persistent high-growth firms

The 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. In fact, setting aside a discussion of possibly alternative proxies of size (in terms of assets, employment, sales or physical output) the literature offers a variety of criteria to classify a firm as high-growth. These criteria are not always consistent. At the same time, and perhaps more importantly, there is not really an attempt to define persistence in a commonly accepted way. Previous studies share the basic intuition that a persistent high-growth firm must experience high-growth consecutively for some time steps. The empirical operationalization of this notion involves either estimating the autocorrelation in the top quantiles of the growth rates distribution or studying the probability matrix that describes the transitions across different rankings in the growth rates distribution over time.

But, because of the different patterns of high-growth that exist in reality, different methodologies lead to the measurement of substantially different notions of persistence. Figure 1 provides examples of different growth trajectories one can observe (over a span of six years, i.e. the time-length in our data, as explained below). Firm A is a "one-hit wonder" firm that makes a big jump in one year and then remains stable without growing anymore. Firm B also experiences a big growth performance in the initial years, but she then starts losing market shares continuously over the subsequent years. Firm C is a highly unstable firm that grows and shrinks repeatedly over the period. Firm D constantly grows over time, and it does so through repeated big jumps.

If one just compare initial and final size, all these firms can be considered as high-growth firms over the observed time period, since they all experience a big increment in their size. At the same time, however, these firms are rather different in terms of the persistence of their outperforming behavior. Intuitively, Firm D seems a natural candidate as a "truly" persistent high-growth firm: it constantly makes big positive contributions, and therefore seems an attractive subject for private investors and policy makers concerned in, e.g. job or value creation. Other patterns might not be so desirable. Growth of Firm A seems to have reached an halt after one year: there is little hope for future positive contribution beyond the initial

[2] One could also refer to managerial literature on resource-based or capability-based view of the firm to search for other determinants of growth, high-growth and persistent high-growth. These theories offers complementary explanations, but we do not have data to measure any of these more detailed firm characteristics.

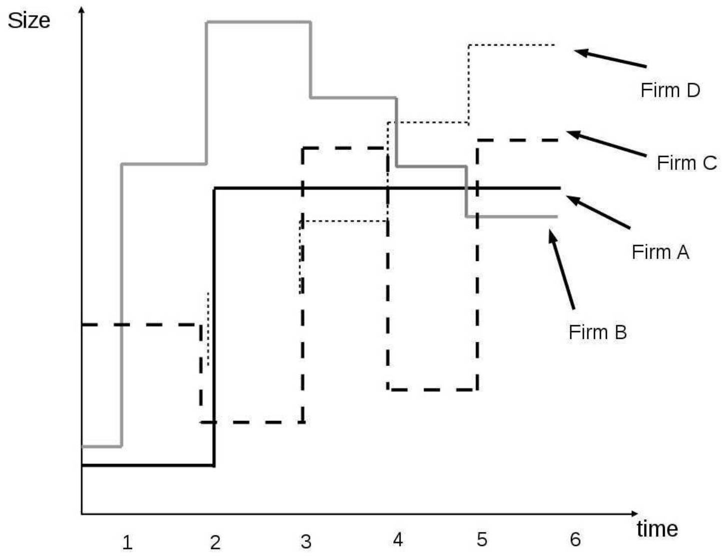

Figure 1: Examples of different High-growth patterns over time. Time is on the horizontal axis. Different lines represent different growth patterns across a window of six years.

big positive jump. Firm B and Firm C can even be considered as problematic, as their growth patterns are likely producing lay-offs and/or value destruction over the period.

A definition of persistence of high-growth based on autocorrelation of annual growth rates would be particularly misleading. Indeed, Firm C is likely to exhibit positive autocorrelation as Firm D does, but with quite contrasting implications for policy. In this sense, the autocorrelation of growth, or even autocorrelation of high-growth, captures a short term and quite restricted concept of persistence. We seek instead to provide a definition which is at the same time more general and more precise, capturing firms that outperform other firms continuously over a reasonably long number of years, at least within the time constraint imposed by the data.

We adopt the following definitions. We divide the time span available in the data into two periods: the two initial years are exploited to measure "initial" firm characteristics (efficiency, profitability, financial status), while we reserve the subsequent six years to distinguish simple high-growth episodes from patterns of "truly continuous" high-growth. Accordingly, to identify the group of 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. Next, 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 PHG 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 provide more details on the actual application of these criteria to the data in the next Section. We here want to highlight three general implications of our approach.

First, 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.[3]

[3] Sales and employment are indeed the most frequently chosen size proxies in the literature. They are

Second, the strategy to identify HG firms through annualized average growth over more than one year is in line with most of the literature, and reflects the already mentioned 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. In previous studies, the number of years considered vary from 3 to 6 years, but the main idea is common. 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 high-growth a firm that hires at least 100 employees) or in relative terms, that is looking at percentage growth over time. Our definition follows the latter approach. Absolute growth implies a bias towards larger firms, whereas the percentage measure allows smaller firms to enter the HG group.

Finally, notice that the "four-out-of-five" years of high-growth required to qualify as a PHG firm implies that there can be PHG firms that are not HG firms. This would be the case, for instance, of a firm remaining in the top 10% of the yearly growth rates distribution for four years, but then having such a deep decline in the remaining fifth year that the same firm falls outside the top 10% of the annualized average growth rate. This consideration motivates the choice of the estimation methods that we make in the regression analysis of Section 6.

4 Data and variables

In this Section, we present the data sources and the working sample, and provide details and descriptive statistics about the different growth status and about the set of variables adopted to proxy for firm economic and financial characteristics.

Sources and sample

We draw upon firm-level information in AMADEUS, a well known and widely used commercial database maintained 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. In order to have a time interval with a good coverage of the variables of interest in all countries, we restrict our analysis to 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, since we will run a comparative analysis across different groups of surviving firms.[4] All the firms are classified according to their sector of principal activity, disaggregation up to 2-digits of NACE 2008 classification. The present study considers both manufacturing and services, covering a final sample of 55,454 firms.[5]

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).

[4]In the empirical literature on firms dynamics the survival bias is often referred to as *attrition bias*. To be precise, we should not say that we compare 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.

[5]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.

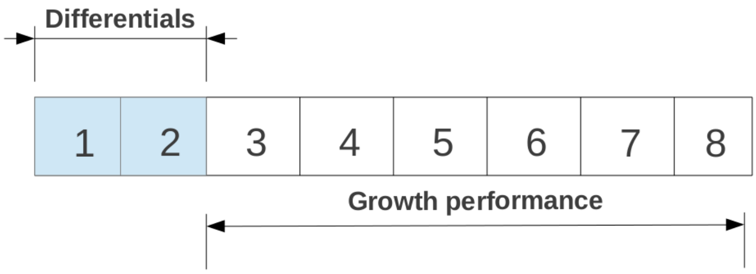

Figure 2: Partitioning of the sample time-period. Differences in firm attributes are measured in the first two years (2004-2005), while growth patterns are evaluated over the subsequent six years (2006-2011).

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 reported in the Appendix.

HG and PHG status

As mentioned, out of 8 years of data, we exploit the last 6 years (2006-2011) to classify firms according to their different growth status (see Figure 2). Specifically, over the second period, we define 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 in the last term 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.[6]

Next, we apply our definitions of HG and PHG firms as presented in Section 3 above, and 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). Of course, if there is perfect serial correlation in growth rates, then all HG firms are also PHG firms.

Tables 1 and 2 show the number of HG and PHG firms by country and sector of activity, as resulting from the identification of growth status over the period 2006-2011. The incidence of

[6]The normalization implicitly removes common trends, such as inflation and business cycles effects in sectoral demand. This is in line with many previous studies on firm growth. Also notice that 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 estimates are stable over the years of the sample period.

Table 1: Number and percentage of HG and PHG 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
		15%	1.6%		15%	0.96%		14%	1.3%		13%	1.6%

Table 2: Number and percentage of HG and PHG 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
		14%	2%		15%	1.5%		14%	1.7%		13%	1.6%

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 ranges 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 reveals some degree of serial correlation in employment and sales growth rates. We also observe a relatively higher incidence of PHG firms within services than within manufacturing.

We are aware of the arbitrariness involved in the choices made to define HG and PHG firms, and we thus performed a series of robustness checks. First, we have verified that our main empirical findings do not change if we identify HG and PHG firms based exclusively on employment or exclusively on sales. Second, somewhat questionable is our choice to consider the top 10% of annualized average growth as the threshold defining the group of HG firms. Therefore, we have experimented with less restrictive definitions appearing in the literature (top 15%), and the main conclusions from the empirical analysis do not change. Finally, we have experimented with changing the number of years a firm needs to pass the 10% threshold in order to be classified as a PHG firm. On the one hand, results do not change if we apply a less stringent criterion and define as PHG companies those firms passing the 10% threshold for just 3 out of 5 years.[7] On the other hand, a more restrictive criterion imposing that PHG firms should pass the threshold in 5 out of 5 years, substantially reduces the number of PHG firms, making the statistical analysis unfeasible.

Firm characteristics

The set of firm attributes that we seek to correlate with growth status includes indicators of structural firm performance (productivity, profitability and financial conditions), together with the two demographic attributes (size and age) more traditionally investigated within the literature on high-growth firms.

We compute Total Factor Productivity (TFP) through the IV-GMM modified Levinsohn-Petrin estimator developed in Wooldridge (2009).[8] 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 in a given year, computed as the ratio between interest expenses and total sales (IE/S), and a standard measure of leverage (LEV), computed as the ratio between total debt and total assets. Age of the firms is computed exploiting the available 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 8.

Table 3 provides basic descriptive statistics in three reference years. The broad picture reflects well known differences across the countries. TFP displays indeed stable patterns over time, with UK, France and Italian companies displaying higher average efficiency than Spanish firms. 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 also reveal the fingerprints of the current financial crisis in a sharp decrease in the last reported year, common to all countries, even if the decline is more moderate 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

[7]The number of PHG firms increases, but it never exceeds the 5% of the total population, depending on sector or country.

[8]The estimates are performed pooling firms within the same 2-digit 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 the instrument to control for endogeneity of labour inputs. As an alternative measure of efficiency, 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 work.

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	4.53	0.74	4.69	0.74	4.64	0.75
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 as in Wooldridge (2009). Return on Assets (ROA) as operating margins-to-assets ratio. Ability to meet debt services 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.

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 mean leverage is higher than in manufacturing, in all countries, suggesting larger debt exposure (relative to assets) 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 that 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. Yet, we do have young firms in the sample, and we indeed observe variation across countries, with Spanish firms on average younger, reflecting the typical structure of this economy.

5 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 HG, PHG and "other" firms, by applying the Fligner and Policello

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. Considered firm attributes are: Return on Assets (ROA) as operating margins-to-assets ratio; ability to meet debt services as interest expenses over sales (IE/S); Leverage (LEV) as total debt over total assets; Total Factor Productivity (TFP) via the modified Levinshon-Petrin estimator as in Wooldridge (2009); Age as computed from year of foundation; and size as annual sales. HG firms as the benchmark group: a positive and significant FP statistic means that HG firms dominates. Asterisks denote significance levels: * $p < 0.01$, ** $p < 0.001$.

(1981) test (hereafter, FP) of stochastic equality between two empirical distributions. While usual tests try to assess distributional 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 in fact present in our data.

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 across the compared groups.

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: a positive FP statistic in this case is in agreement with the expectation that HG firms are more profitable. No differences are detected in the other countries, irrespective of the sector. Second, we find similarly lacking evidence of statistically significant differences in terms of efficiency. The exceptions in this case are found within Italian manufacturing, where HG firms have lower TFP in distribution than the group of other firms, and within Spanish services, where HG firms appear as more efficient. 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

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. Considered firm attributes are: Return on Assets (ROA) as operating margins-to-assets ratio; ability to meet debt services as interest expenses over sales (IE/S); Leverage (LEV) as total debt over total assets; Total Factor Productivity (TFP) via the modified Levinshon-Petrin estimator as in Wooldridge (2009); Age as computed from year of foundation; and size as annual sales. HG firms as the benchmark group: a positive and significant FP statistic means that HG firms dominates. Asterisks denote significance levels: * $p < 0.01$, ** $p < 0.001$.

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 most cases, with the only exception of UK services, we obtain (strongly significant) evidence 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, hence they are not completely credit rationed, but they possibly 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 relative to own assets is clearly standing out as a distinguishing feature of high-growth firms.

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, in all countries and across both manufacturing and services. Second, we cannot detect any significant difference in the distribution of TFP in practically all country-sector combinations, except for the case of Italian manufacturing where PHG firms tend to be less productive than HG firms. Third, the estimates reveal that leverage displays some, albeit very limited, discriminatory power. PHG firms are more indebted, in proportion to their total assets, in Italy and in the UK in manufacturing, and the same holds also in services if we pool the data altogether across countries. Finally, the results cast also doubts on the role of size and age, emphasized in previous studies. In manufacturing, PHG firms tend to be younger and smaller in Italy and Spain, while we cannot reject the equality of age and sales distributions in the case of French and UK firms. In services, age plays a role in Spain and in the UK, again with the expected sign, while size only matters in Italy and Spain.

Notwithstanding these exceptions, a fair summary of the findings is that persistent high-

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) are: Return on Assets (ROA) as operating margins-to-assets ratio; ability to meet debt services as interest expenses over sales (IE/S); Leverage (LEV) as total debt over total assets; Total Factor Productivity (TFP) via the modified Levinshon-Petrin estimator as in Wooldridge (2009); Age as computed from year of foundation; and size as annual sales. Bootstrapped standard errors (100 runs) in parenthesis below the coefficients. Asterisks denote significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

growth firms do not differ in any systematic way from high-growth firms.[9]

6 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,

[9] A drawback of the FP test, common to other non-parametric tests, is the need to have a relatively large number of data points to achieve the same power of parametric tests for difference in means. However, our conclusions from the FP test remains unchanged if we apply a standard two-sample Student's t test for equality of means across heteroskedastic samples, or the Wilcoxon-Mann-Whitney test for equality of medians.

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 modeled as a function of a vector $\mathbf{v}_i$ of explanatory variables

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

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). Similarly to 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 initial firm characteristics (measured in the first two years of the sample period) and growth status (measured in the second part of the sample period) reduces potential simultaneity bias.

We estimate a Multinomial Probit model with independent idiosyncratic components across the alternatives, via full maximum likelihood. This estimation method is a natural choice since, by construction, the growth status is unordered (we might have inverted the assignments without any effect) and we cannot hold the independence from irrelevant alternatives assumption required by (Multinomial or Mixed) Logit-type estimators. Also, ordered (probit or logit) models are not attractive here, since they assume that there is a unique, common underlying mechanism connecting firm characteristics to different growth patterns across HG and PHG firms, so that the observed PHG or HG status are just the result of a differential reaction to different values of the independent variables. Instead, the Multinomial Probit allows the choice to be PHG to be independent from the probability to be HG, and thus we can let the data tell us, rather than assuming, whether PHG status can be considered as the result of a stronger "treatment" effect.[10]

Despite some computational burden related to the underlying specification of a Multivariate Normal distribution, the estimation outcome of the Multinomial Probit 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 be spurious.[11]

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 reports 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 an HG firm.

[10] Recall indeed that the two sets of PHG and HG firms are non-nested. See also Section 9 for a discussion of alternative estimation methods.

[11] 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. As a further check, we have also computed 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.

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) are: Return on Assets (ROA) as operating margins-to-assets ratio; ability to meet debt services as interest expenses over sales (IE/S); Leverage (LEV) as total debt over total assets; Total Factor Productivity (TFP) via the modified Levinshon-Petrin estimator as in Wooldridge (2009); Age as computed from year of foundation; and size as annual sales. Bootstrapped standard errors (100 runs) in parenthesis below the coefficients. Asterisks denote significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

In Column 1, we pool all the data across countries. The signs and the significance obtained for the "other firms" imply that HG firms are more profitable, pay higher interests per unit of sales, have a larger debt-to-asset ratio, and are more 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 confirm the usual finding that both age and size play a significant role, with HG firms being younger older and smaller. Age, in particular, displays the stronger association (coefficient is 0.174), followed by size (0.147). TFP and Leverage have smaller coefficients (about 0.10 and 0.12, respectively), while ROA and IE/S play a secondary role, with much smaller coefficients (about 0.02) and weaker statistical

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) are: Return on Assets (ROA) as operating margins-to-assets ratio; ability to meet debt services as interest expenses over sales (IE/S); Leverage (LEV) as total debt over total assets; Total Factor Productivity (TFP) via the modified Levinshon-Petrin estimator as in Wooldridge (2009); Age as computed from year of foundation; and size as annual sales. Bootstrapped standard errors (100 runs) in parenthesis below the coefficients. Asterisks denote significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

significance.

The picture changes completely when we look at the estimated association of regressors with the odds of falling into the PHG category. In this model, indeed, only age and size have a significant coefficient, matching previous evidence that PHG firms are more likely to be younger and smaller companies than HG firms. By contrast, we fail to detect any statistically significant association between PHG status and none of the firm structural characteristics. 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 results for the odds of being "other firms" vs. being HG, 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 estimates of about 0.29 and 0.22, respectively). 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 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. In manufacturing, efficiency and leverage emerge, together with size and age, as the key characteristics distinguishing HG from "other firms": HG firms are generally more efficient, more indebted relatively to own assets, and also smaller and younger, in all countries but the in the UK. Profitability has a role only in Italy, while IE/S is never significant. If we move to persisitnece, we observe, once again, that PHG firms do not differ systematically from HG firms along any of the included dimensions, with the only exception of size in Italy.

The picture is quite similar when we look at services. The main differences with manufacturing are that in services HG firms have significantly higher IE/S than "other firms" in Spain and France (not in Italy and in the UK), while profitability is never significant, and we loos the statistically significance of TFP in France. But, more importantly, 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.

The general conclusion is that the drivers of growth predicted by the theory, productivity and leverage in particular, play some role in discriminating high-growth patterns, whereas they do not discriminate persistent from "simple", 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. Indeed, most of the omitted variables one can think of (e.g., unmeasured capabilities or managerial ability) are all likely to positively correlate with both growth performance and included regressors.[12]

7 The role of innovation

The recent empirical literature on high-growth firms suggests that innovativeness represents 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 innovative activity (R&D or patenting). 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

[12]An issue of reverse causality may still be present if one thinks that initial firm characteristics in years the 2004-2005 are not predetermined with respect to growth status in the following years. Although our empirical design does not allow to test this assumption, it seems reasonable that this concern is only valid for the very first years of the 2006-2011 period, and the relatively long period we use to define the growth status should cure for most of this issue.

Table 9: Multinomial Probit with Intangible assets - 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) are: Return on Assets (ROA) as operating margins-to-assets ratio; ability to meet debt services as interest expenses over sales (IE/S); Leverage (LEV) as total debt over total assets; Total Factor Productivity (TFP) via the modified Levinshon-Petrin estimator as in Wooldridge (2009); firm age (AGE) as computed from year of foundation; firm size (SIZE) as annual sales; and Intangible Assets (INTASS). Bootstrapped standard errors (100 runs) in parenthesis below the coefficients. Asterisks denote significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

(INTASS) as a firm-level proxy for innovativeness.[13]

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 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

[13]The Amadeus data 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 (despite limitations) in innovation studies (see, e.g., Hall, 1999).

and significant coefficient in the odds of being "other" vs HG firms, at least in some cases (in the pooled analysis, in Italy and in the UK). This is 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. From the estimated coefficients on intangibles, innovativeness does not have any discriminatory power in manufacturing, while there is some role in services, as we indeed find that HG firms are more innovative than "other firms" in Italy and in the UK, and that PHG firms tend to be more innovative than HG firms in France, but at very low levels of statistical significance.[14]

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.

8 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. Indeed, 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 divide the firms into age and size classes, and then we repeat the Fligner-Policello test of stochastic dominance to compare the empirical distribution of productivity, profitability and financial indicators across HG and PHG firms within each size and age class.[15] In order to have a reasonable number of observations in each class, we build two size classes based on employment according to 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 aged-Old firms with age > 5 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 (in Table 12), we find that young HG firms outperform young PHG firms in terms of TFP in Italy, whereas mid-old HG firms

[14] 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 KIS vs. non-KIS 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 few cases, and thus provide a weak contribution to predict persistence of high-growth status.

[15] 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.

Table 10: Multinomial Probit with Intangible assets - 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) are: Return on Assets (ROA) as operating margins-to-assets ratio; ability to meet debt services as interest expenses over sales (IE/S); Leverage (LEV) as total debt over total assets; Total Factor Productivity (TFP) via the modified Levinshon-Petrin estimator as in Wooldridge (2009); firm age (AGE) as computed from year of foundation; firm size (SIZE) as annual sales; and Intangible Assets (INTASS). 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: Multinomial Probit with Intangible assets - Services

	Pooled (1)	Italy (2)	Spain (3)	France (4)	UK (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) are: Return on Assets (ROA) as operating margins-to-assets ratio; ability to meet debt services as interest expenses over sales (IE/S); Leverage (LEV) as total debt over total assets; Total Factor Productivity (TFP) via the modified Levinshon-Petrin estimator as in Wooldridge (2009); firm age (AGE) as computed from year of foundation; firm size (SIZE) as annual sales; and Intangible Assets (INTASS). 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. Considered firm attributes are: Return on Assets (ROA) as operating margins-to-assets ratio; ability to meet debt services as interest expenses over sales (IE/S); Leverage (LEV) as total debt over total assets; and Total Factor Productivity (TFP) via the modified Levinshon-Petrin estimator as in Wooldridge (2009). Young firms are defined as ≤ 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: * $p < 0.01$, ** $p < 0.001$.

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 between HG and PHG firms in Italy also holds if we compare TFP within size classes, 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 shows 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 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 considered here does not provide any robust discriminatory power in distinguishing persistent high-growth firms.

9 Alternative regression models

A major implication of our empirical design is that standard panel regression models are not viable. In principle, one way to exploit the panel dimension of the data would be to define HG status on a yearly basis, take this as the dependent variable and see if firm attributes have an impact on the autocorrelation of the yearly HG status. Or alternatively, one could estimate quantile auto-regression in yearly growth rates, and see whether firm attributes interact with

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. Considered firm attributes are: Return on Assets (ROA) as operating margins-to-assets ratio; ability to meet debt services as interest expenses over sales (IE/S); Leverage (LEV) as total debt over total assets; and Total Factor Productivity (TFP) via the modified Levinshon-Petrin estimator as in Wooldridge (2009). Young firms are defined as ≤ 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: * $p < 0.01$, ** $p < 0.001$.

the autoregressive coefficient in the top quantiles. However, as mentioned, both strategies would limit the analysis to a very specific notion of persistence, based on the autocorrelation structure of the growth rates, which is unsuitable to capture a more general and longer-run notion of persistence in high-growth. Thus we decided not to pursue any robustness check in that direction.[16]

There is however a different robustness check that is worth pursuing. Recall indeed that the Multinomial Probit is theoretically superior in our empirical setting, since the two categories of HG and PHG firms, as we define them, are non-nested. In fact, according to our definitions, a company can be a PHG firm without falling at the same time in the HG group (see left plot in Figure 3). The Multinomial Probit allows for this grouping as it does not place restrictions on the structure of error terms across groups. However, in practice, only a quite small number of PHG firms are not HG firms in the data (76 firms in total). We therefore explore sensitivity to the choice of the estimation method by applying an alternative econometric specification where we impose that PHG firms are a subset of the HG category, as if the decision to be PHG is conditional upon the decision to be HG (as in the right plot of Figure 3).

Such different structure, naturally leads to a two-step conditional probit. To implement that, we assign to the group of "other firms" all the firms which, according to our definitions, happen to be PHG, but not HG. Next, we estimate a first probit for the probability to be selected in the HG set (which now includes the PHG set)

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

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

[16]In any case a large literature already did, as discussed in Section 2.

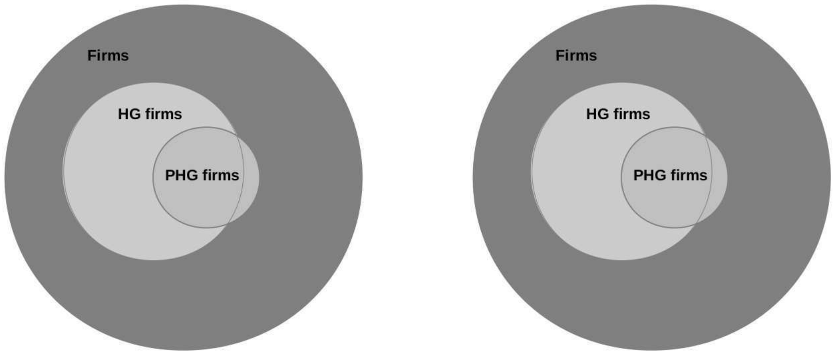

Figure 3: Definition of HG, PHG and other firms. Left panel: PHG is not a subset of HG. Right panel: PHG is a subset of HG

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

being in the HG set

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

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, this new specification represents the restriction of the Multinomial Probit to a degenerate error variance-covariance matrix.

In Table 14 we show results for the specifications pooling the data across manufacturing and services.[17] 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, thus confirming our general conclusion about the weak power of economic and financial factors in discriminating persistence in high-growth performance.[18]

10 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 they did no attempt 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 leverage in particular) are associated with high-growth. However, none of the supposedly key drivers of growth systematically stands 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. Finally, we do not fully corroborate previous evidence that firm size and age are key features of persistent high-growers, although persistently high-growers are younger and smaller in some country-sector pairs.

Of course, there are 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 capabilities, organizational characteristics, 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

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

[18] In unreported estimates we have repeated the two-step conditional probit for all the other specifications presented in the previous sections. Results are in accordance with the Multinomial Probit analysis.

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. In particular, the lacking association between efficiency and persistence in high-growth performance suggests that supporting high-growth firms could not necessarily favor firms that are able to contribute to the overall competitiveness of sectors and countries.

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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.