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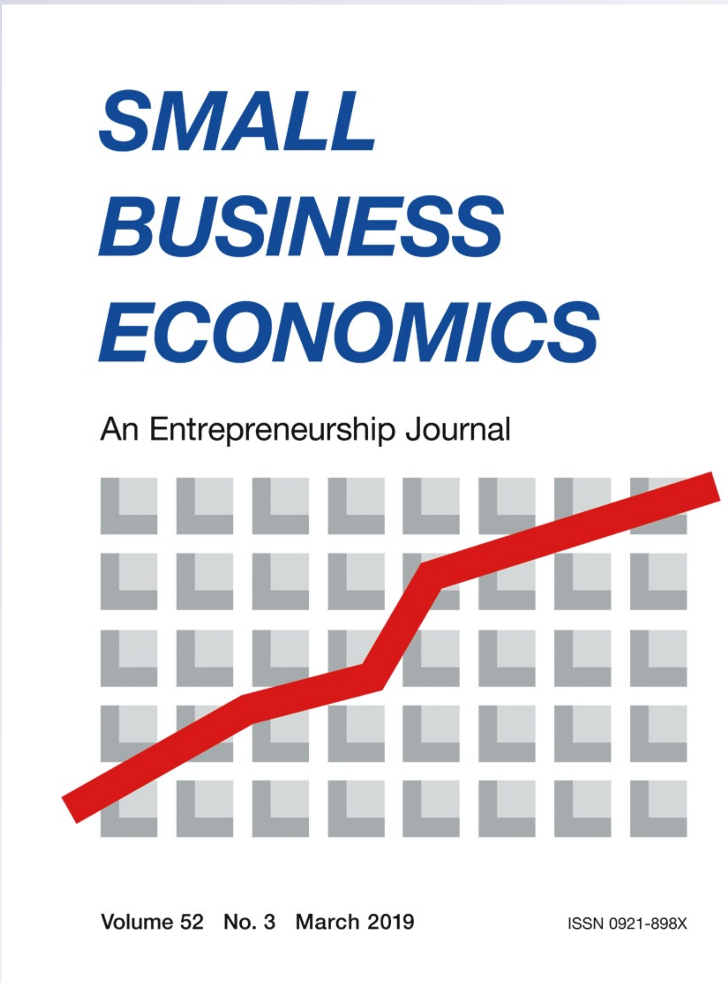

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Abstract This article explores the association between persistence of high-growth and crucial dimensions of firm structure and performance (productivity, profits, investment patterns, innovation, and financial structures) to shed light on what makes a persistent high-growth firm. We employ a multidimensional definition of a high-growth firm that simultaneously accounts for growth of sales and employment, and design an empirical strategy that seeks to capture the "long-run" ability of high-growth firms to replicate their high-growth performance over time. Exploiting a large panel covering the period of the China's miracle, we find that none of the considered firm attributes stands out as distinctive feature of persistent high-growth. This finding casts doubts on the long-run contribution of high-growth firms, in turn challenging the long-run effectiveness of policies supporting the creation and expansion of such firms.

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1 Introduction

The identification of the characteristics that make a firm able to provide extraordinary contribution to growth and employment creation is at the center of the attention of practitioners and policy makers around the world. Achieving high-growth, especially in terms of sales and market shares, is often considered as one of the most important factors in entrepreneurial orientation (Covin et al. 2006), and policies to support the creation and the performance of gazelles, i.e., small-, young-, and, more generally, high-growth firms are adopted in several countries. They have also received new attention as a driver of economic recovery and employment growth after the global crisis (see Birch and Medoff 1994; Davidsson and Henrekson 2002; Acs and Mueller 2008; Henrekson and Johansson 2010; Acs et al 2011; Coad et al 2014).

The academic literature on high-growth firms is vast, with contributions coming from different research areas, at the intersection between firm-industry dynamics, entrepreneurship, and management studies. In brief, and without claiming to be exhaustive, the development of this literature proceeded mostly through empirical studies, seeking to identify the factors that ease or hamper the creation and the development of high-growth firms, both in terms of structural conditions of the environment in which firms operate (institutional and geographical factors; characteristics of input, output, and credit markets; role of network and externalities; public policies of various kind) and in terms of the firm-specific characteristics that associate with high-growth events. Of course, the empirical efforts were guided by a large number of theoretical contributions to the conceptualization of entrepreneurship—from Schumpeter's view on the different sources and modes of entrepreneurial innovation across industries to the classical works by Baumol (1990, 2010)—as well as by models of firm growth and industry dynamics with heterogeneous firms, from very different traditions, such as neoclassical models of equilibrium dynamics (as in Jovanovic 1982; Hopenhayn 1992; Ericson and Pakes 1995; Luttmer 2007; Clementi and Hopenhayn 2006), or evolutionary disequilibrium theories (as, among others, in Nelson and Winter 1982; Winter 1984; Dosi et al. 1995; Metcalfe 1998; Bottazzi et al. 2001), in turn sharing with management scholars the notion of routines and dynamic capabilities of the firm as the key drivers of sustained comparative advantage and growth over time (Teece and Pisano 1994; Teece et al. 1997; Dosi et al. 2001; Pisano 2015).

We now know a lot about the role of a number of institutions and policy measures such as taxation of entrepreneurial income, incentives for wealth accumulation, wage-setting and labor market regulation, and geographical knowledge spillovers (see, among others, Davidsson and Henrekson 2002; Acs and Mueller 2008; Garsaa and Levratto 2015), while a number of firm-specific attributes have been studied as distinguishing features of high-growth firms (see Coad and Hölzl (2012), for a more extensive review). In this respect, the meta-analysis of the literature conducted in Henrekson and Johansson (2010) identifies the established stylized facts that high-growth firms tend to be younger, smaller and ubiquitous in all industries, confirming the seminal study by Schreyer (2000). A recent debate centers around the relative role of the two key demographic characteristics, namely size and age, as key drivers of high-growth and extraordinary employment creation. While most studies identify high-growth firms as small and young, Henrekson and Johansson (2010) emphasize that larger gazelles are also important job contributors in absolute terms. Newness or young age was found as the key characteristic supporting high employment growth in the USA before the 2000 by Haltiwanger et al. (2013), although the contribution of start-ups and young businesses declined in the following 10 years (see Decker et al., 2016). On the contrary, Acs et al. (2011) find that the average high-impact firm is around 25 years old when it makes a significant contribution to the economy (see also Lawless (2014) on Irish firms and Grazzi and Moschella (2017) on Italian firms).

Two further characteristics that seem to play a major role in high-growth patterns are export status and ownership structure. From the internationalization and trade perspective, we know that many high-growth firms are indeed exporters and their strategies are globally oriented (Robson and Bennett 2000). Also, there is evidence that different ownership types associate with differential growth performance: although the average growth rates of domestic and foreign firms do not necessarily differ (see the meta-analysis in Bellak (2004)), state-owned firms usually perform worse than private firms, and foreign-owned firms are more likely to exhibit fast-growth (Beck et al. 2005).

Beyond demographic factors such as size, age, ownership or export status, theories of firm-industry dynamics point at wide heterogeneities in productivity and profitability, mediated by financial conditions and innovation capacity as the crucial structural dimensions of performance that sustain growth (see Dosi 2007). In the empirical literature connecting such structural dimensions of performance with high-growth, innovativeness occupies a disproportionate share of available studies. High growth has been related to different innovation activities undertaken at the firm level, such as R&D, patenting, product vs. process innovation, external sourcing of knowledge, and other indicators usually available through innovation surveys (see, among others, Coad and Rao (2008), Hölzl (2009), Stam and Wennberg (2009), Segarra and Teruel (2014), and Bianchini et al. (2016)), also exploring the mediating role of age in connecting innovation and growth (see, e.g., Huergo and Jaumandreu (2004), Coad et al. (2016)). Results show that innovative efforts are indeed important for the growth performance of firms in the top quantiles of the growth rate distribution, while innovation shows weak relations with growth of the average firm (see Audretsch et al. (2014), for an exhaustive survey).

The role of other structural characteristics, such as efficiency, availability of profits, patterns of investment and access to finance as determinants of high-growth is less investigated. Concerning productivity results are mixed. Du and Temouri (2015) find, for the UK, that firms in both manufacturing and services are more likely to become high-growth firms when they exhibit higher productivity growth, and Bianchini et al. (2017) show that high-growth firms are more efficient in Italy and Spain. On the other hand, Daunfeldt et al. (2010) detect an insignificant or even negative association between productivity growth and high-growth for Swedish firms. There is some evidence that high-growth firms are more profitable than other firms (see Coad et al. (2011), Bianchini et al. (2017)), although not many studies are available on the subject. Profits and other proxies of internal finance, such as cash flow, are extensively analyzed within the literature on financial constraints to investment and growth. In fact, notwithstanding internal finance and credit rationing are critical to the growth performance of young and small enterprises (see Oliveira and Fortunato (2006) and Bottazzi et al. (2014), for reviews), only few studies relate financial conditions and investment dynamics to high-growth. Bianchini et al. (2017) show that high-growth firms tend to face higher interest burden and to rely more on external credit than on their own resources, a finding that may be interpreted as a signal of past ability to access credit, but also as a worrying feature for future viability of the business.

Against this background on the characteristics and drivers of high growth, this paper contributes to a more recent literature that investigates the ability of high-growth firms to sustain their extraordinary growth performance consistently over time. Persistent high-growth firms represent much more promising candidates to provide substantial contributions to economic performance of sectors and countries than "simple" high-growth firms that exhibit just one or two spurts of high growth. Indeed, the great deal of scholarly and policy attention devoted to the creation of and support to high-growth firms implicitly assumes that high-growth firms are an engine of growth that lasts over time. Policy makers, in particular, are more likely to search for firms that continuously create high value and large employment, than they are to support the experimentation and private returns of some firms that grow spectacularly for just a short period of time.

We know very little about the persistence of high-growth events, however, and even less about what makes a firm a persistent high-growth firm. On the one hand, some studies even challenge the very existence of persistent high-growth firms. Hölzl (2014) and Daunfeldt and Halvarsson (2015) show that high-growth firms are mostly "one-hit wonders" that do not replicate their high growth over time, echoing theories of firm growth as essentially stemming from luck (Barney 1997). Delmar et al. (2003) and Capasso et al. (2014) show that persistent outperformers and "super relative growers" do exist, but they are relatively rare. On the other hand, available empirical studies characterize persistent high growth firms just in terms of size and age, with mixed results. Coad (2007) and Coad and Hölzl (2009) find that small high-growth firms display negative growth autocorrelation, whereas large and established companies achieve smoother dynamics. Conversely, Capasso et al. (2014) conclude that persistent outperformers are more often present among micro firms.

We provide a twofold contribution to the study of high-growth persistence. Our main research question is to address whether more structural factors, such as productivity, profits, investment, financial conditions, and innovativeness, stand out as distinguishing features of persistently high-growing firms, beyond demographic characteristics. To our knowledge, only two papers address the same question. Guarascio and Tamagni (2016) show that persistence in innovation does not affect growth persistence of high-growth firms, measured as the yearly autocorrelation of sales growth in the top quantiles of the growth rate distribution in a sample of Spanish firms. Bianchini et al. (2017) provide a more comprehensive analysis, addressing a set of firm characteristics similar to the one we consider in this paper, including productivity, profitability, intangible assets, and financial conditions, beyond size and age. They identify persistent high-growth firms over a relatively long-run (4 years) perspective and show that persistent high-growth firms do not differ from "simple" high-growth firms along any of the dimensions of structure and performance, in a sample of firms active in manufacturing and services in Italy, Spain, France, and the UK. We share with Bianchini et al. (2017) the emphasis on the need to look at relatively long-run perspective, beyond 1-year auto-correlations, but provide a different econometric framework to assess whether firm structural characteristics contribute to the probability that a high-growth firm remains high-growth over a relatively long span of time.

As a further important contribution, we address our main question in the context of Chinese manufacturing firms. Previous literature, not only on high-growth persistence, but more generally also on high-growth firms is dominated by studies on advanced economies. Analysis of high-growth dynamics in developing economies are rare, and the few exceptions focus on the institutional obstacles to entrepreneurship and growth that may affect those countries, such as underdeveloped infrastructure or weaknesses in the financial or legal system. Krasniqi and Desai (2016), for example, offer country-level analysis of the importance of formal and informal institutions on the share of high-growth firms in the economy, across 26 transition countries. Firm-level analyses in developing context are even more scant, often for lack of data. Goedhuys and Sleuwaegen (2010)'s study of Sub-Saharan countries confirms the importance of technology and infrastructure (access to the Internet from own website, in particular) for high-growth entrepreneurship. Santi and Santoleri (2017) show that process innovation positively affects growth of top-growing Chilean firms, while product innovation does not.

The case of Chinese manufacturing and, in particular, the period covered by our data (1998–2007), corresponding to the years of the extraordinary materialization of the "China miracle," represent an extremely interesting test-bed for understanding the contribution of firm's structural characteristics to high-growth persistence. That phase of unprecedented expansion was indeed boosted by reforms and direct policies undertaken by the Chinese authorities favoring the development of virtuous dynamism in the economy, supporting new entrepreneurship and private firms, although within the boundaries of a state-managed economy. Understanding the factors distinguishing *persistent* high-growth firms—which are likely to capture the dynamism of "true entrepreneurship"—from simple one-hit wonders in that period might also help to facilitate policy measures to sustain the recovery of the Chinese economy after the global crisis, and the process of Chinese economic catching-up in the long run.

In Section 2, we provide an overview of entrepreneurship and high-growth dynamics in the context of China. In Section 3, we present and motivate the empirical framework that we adopt to assess the interplay between persistence of high growth and firm characteristics. Section 4 shows descriptive evidence on high-growth, high-growth persistence, and evolution of main firm characteristics. In Section 5, we present our main findings on the influence of structural firm characteristics upon the probability to persistently remain high-growth, while in Section 6, we dissect the specific role of age, size, and state-ownership. Section 7 concludes.

2 The Chinese context

The extraordinary performance of the Chinese economy, especially over the period that we consider in this study, has obviously attracted attention of scholars and policy makers. Increasing availability of micro-data at the firm level allowed for a characterization of the key features of industrial dynamics in that period, highlighting the role of virtuous transformation and learning of domestic firms, the differential contribution of state-owned vs. private firms, also regarding access to finance and the role of innovation in survival and growth (see Yu et al. (2015), Guariglia et al. (2011), and Zhang and Mohnen (2013)). Indeed, the "China miracle" entailed a major process of increasing returns through learning and accumulation of knowledge and technological capabilities based on firms that are highly heterogeneous, in terms of all the dimensions of firm performance and characteristics that we analyze in this study (Yu et al. 2015, 2017).

Explicit consideration of patterns and determinants of high-growth dynamics has not received attention, however. Most of existing literature frames the dynamism of the Chinese economy around the concept of entrepreneurship, referring to as those creations and newness initiated by Chinese citizens or domestic firms over the last 15–20 years, and the socio-political transformations that sustained them (Yang and Li 2008; Li 2013).

The development of entrepreneurship in China went through three phases (Li 2013), characterized by the emergence and prominent role of different types of new firms: the first stage (1978–1992) sees the birth and flourishing of township-and-village enterprises, and the initial appearance of private firms; the second stage (1992–2000) features the rapid growth of non-public firms, promoted by the first signals of political acceptance of the private property (the Deng Xiaoping's "South Tour" in 1992) and the related constitutional amendment in 1999; in the third stage (2000–present), increasingly generous policies were issued to channel private investments, promote small and medium enterprises, and to protect private property. A number of studies on Chinese entrepreneurship extensively focus on the association between the phases of entrepreneurial development and liberalization policies, such as the removal of institutional barriers to private ownership, or easing the access to key resources (finance, labor, and technology) for private firms and SMEs (Chang and MacMillan 1991; Li and Matlay 2006).

Among the three types of entrepreneurship that usually coexist within developing countries—subsistence, catch-up, and frontier entrepreneurship (see Hobday and Perini (2009), Huang (2010))—the vast majority of Chinese entrepreneurships are of the catch-up type. They usually engage in replicative activities, copying and re-producing at competitive costs innovations introduced by others, as it is the case, for instance, with Wanxiang (an automobile supplier) and Geely (the firm that just acquired Volvo). They considerably contribute to the economy through market expansion (within existing areas) and job creation, although they introduce breakthroughs in science and technology at a much lower pace than frontier entrepreneurship firms do.

The prevalence of catch-up firms warns against the potentially misleading implications that may arise from an exclusive focus on start-ups and small firms. As argued by Hobday and Perini (2009), there is a spread mis-conception of the function of new and dynamic firms in catching-up economies: their primary role is to enable technology transfer, learning, and incremental innovation, rather than to trigger "Schumpeterian dynamics" leading to new product and process development, which is instead the main role of entrepreneurship in advance economies. In fact, the evidence on successful firm-level growth from China and other Asian countries shows that large firms, SMEs, and multinational corporations all play a role in entrepreneurial progress. In this sense, our study of the drivers of high-growth persistence shed a different light on Chinese entrepreneurship dynamics than most of the literature on China, which has usually stressed the role of small, innovative start-ups. The extensive dataset available to this study, covering a large part of Chinese manufacturing, represents an ideal setting to ground the understanding of high-growth persistence upon the general background of the rapid catching-up of the Chinese economy.

3 Persistence of high-growth and firm characteristics: an empirical framework

Our key research question is whether a set of firm characteristics, which are theoretically considered as important determinants of firm growth, display in turn an empirical association with the ability to replicate high-growth performance over time. The few previous studies concerned with persistence of high-growth do not offer a shared empirical framework. There exist different, and not at all consistent definitions of what a high-growth firm is. Also, there is no consensus on the very notion of persistence one should adopt, beyond a generic agreement that one should look at firms that are able to maintain their high-growth status, however defined, consecutively over a certain number of years. Definitions and empirical settings are inevitably constrained by the type and nature of the data that different researchers have access to. In this section, after a brief description of the data, we present and discuss our baseline empirical model, and introduce the variables adopted to proxy for key firm characteristics.

3.1 Data

We exploit the firm-level data collected by the Chinese National Bureau of Statistics (NBS), to which we have access for the period spanning the years 1998–2007. The original dataset is a standard business register type of data, largely used in previous studies on Chinese firm-industry dynamics (see, among others, Hu et al. (2005), Fu and Gong (2011), Yu et al. (2015)). It includes all industrial firms with sales above 5 million RMB (around $US 600,000), while firms employing less than eight employees are not recorded, since Chinese firms below that threshold operate under a completely different legal system (see Brandt et al. (2012)). The data cover mining, manufacturing, and public utilities, and each firm is assigned to a sector according to the 4-digit Chinese Industry Classification (CIC) system, that closely matches the Standard Industrial Classification (SIC) employed by the U.S. Bureau of Census.[1] We focus on manufacturing firms only and apply a few cleaning procedures to the original data, as suggested in Yu et al. (2015) in order to eliminate visible recording errors.[2] The final version of the data at our disposal corresponds to the "China Micro Manufacturing" (CMM) panel used in Yu et al. (2015). Next, since measuring high-growth and its persistence requires to follow the same firms over a reasonably long time span, we focus on those continuing firms that are present in the data over the entire period 1998–2007. The resulting balanced panel consists of a working sample of 22,988 manufacturing firms.

3.2 Empirical model

Correlating high-growth persistence with firm attributes involves three problematic issues. First, one needs a definition of high-growth firm. But this is not an easy step, as indeed the literature suggests a number of identification criteria, that differ under several respects. Different size proxies are employed, usually distinguishing between employment and sales, respectively looking at growth in terms of "physical capacity" or in terms of "success on the market." The two growth processes do not necessarily map one into the other, and their determinants can be arguably different, with employment growth more related to labor market dynamics, and sales more related to industrial dynamics. Further, there is not a unique criterion to define "how high" a high-growth jump must be to qualify a firm as a high-growth firm. Different studies distinguish between either absolute or relative extraordinary growth events. This makes a difference, since absolute growth (defining, for instance, as a high-growth firm a firm hiring 200 employees or selling 1ML dollars more) implies a bias toward larger firms, while relative growth (e.g., defining as high-growth a firm that doubles its size) allows more small-micro firms to also qualify as high-growth. Not unrelatedly, it also matters the fact that high-growth is often intended and measured as being in some top percentile of the distribution of growth rates across the firms in a reference group (e.g., firms in the same sector), but results may vary, of course, depending on which percentile one looks at (top 20%, or top decile, for instance). In particular, one has to balance between the need to apply stringent thresholds that more likely define the group of "genuinely top performers," and the possibility that too stringent thresholds (say top 1%) end up identifying a too small number of high-growth firms, preventing any meaningful statistical comparison with other firms. Finally, different approaches exist regarding the time span over which a high-growth event is considered. Starting from the known stylized fact gathered in the empirical literature on Gibrat's Law stating that firm size is a quasi random-walk, and thus, growth itself is quite erratic over time, a single big jump in size in 1 year does not seem enough to characterize persistent high-growth. Most studies evaluate high-growth jumps averaging over some years, typically 3–5 years. However, since this practice may absorb most of the time span available in a typical panel dataset (usually spanning around 10 years), it is not uncommon that high growth is also measured on a yearly basis.

The last consideration links directly to the second major issue we need to tackle, concerning the different notions of persistence that are implicitly or explicitly employed in the literature. Indeed, once a definition of high growth is chosen, there are different ways to evaluate whether a firm replicates its high-growth status over time. The shared basic intuition is that a persistent high-growth firm must experience high-growth consecutively for some time steps. Yet, different empirical operationalizations of this notion exist. A first approach is to estimate the transition probabilities across different quantiles of the growth rate distribution, usually over 1–3 years of transition. Another approach is to estimate quantile regressions to evaluate the degree of growth autocorrelation in the top quantiles of the growth rates distribution, usually taking one or two yearly lags of growth on the right hand side. Both methods allow to quantify the degree of persistence in the data, averaging across firms that over time jumps in and out from top quantiles. They do not provide an identification of a group of persistent high-growth firms, however. Moreover, the implicit notion of persistence is essentially of a

[1] In 2003, the classification system was revised: some sectors were further disaggregated, while others were merged together, but consistency over time is ensured by adopting the harmonized classification proposed in Brandt et al. (2012).

[2] Essentially, we just dropped few firms with negative values in output, sales, value added, fixed assets, and cost of labor.

short-run nature: both approaches define high growth on a yearly basis and look at the probability to remain high-growth 1, 2, or 3 years later. Of course, the main reason is that researchers do not usually have long-in-time panels allowing to capture a more genuinely, long-run definition of persistence of high-growth status. The issue is made explicit and at least partially tackled, within the limitation of their data, in the recent study by Bianchini et al. (2017), that define a group of persistent high-growth firms as those remaining in the top decile of yearly growth rate distributions for at least 4 out of 5 years covered by their data.

A third and final issue pertains the perhaps key question: once a suitable definition of persistent high-growth firms is chosen, how can we identify empirically whether they differ in terms of firm-level attributes? In this respect, the available literature, is at its initial stage, providing essentially only two alternatives. A first approach, within the studies that look at quantile auto-regressions in top quantiles of growth, is to compare the autoregressive coefficient across groups of firms with different firm characteristics, essentially age and size. But, again, this gives an idea about whether these firm attributes have some relation with short-run persistence of high-growth. Bianchini et al. (2017), instead, estimate the effects that a larger set of firm characteristics have on the probability to belong to the group of firms that they a priori define as persistent high-growth firms.

In the absence of a commonly accepted framework, we design an empirical strategy that tries to balance the several trade-offs emerging from previous studies, and inevitably within the limitations imposed by the data available to us.

In brief, we divide the 10 years spanned by our data into sub-periods, identify high-growth status in terms of the average growth experienced by each firm vis-à-vis other firms in each sub-period, and, finally, we capture the "effect" of different firm attributes on high-growth persistence by looking at whether key firm attributes display any statistically significant association with the probability that a firm remains high-growth over two consecutive sub-periods.

More specifically, we proceed as follows. First, we distinguish three non-overlapping sub-periods: period 1 (1999–2001), period 2 (2002–2004), and period 3 (2005–2007). Second, we compute the within-period average growth rate for each firm: $g_{i,1} = (s_{i,01} - s_{i,98})/3$, $g_{i,2} = (s_{i,04} - s_{i,01})/3$, and $g_{i,3} = (s_{i,07} - s_{i,04})/3$, where firm size $S_{i,t}$ is measured as either sales or number of employees, and $s_{i,t} = \log(S_{i,t}) - \frac{\sum_{i\in j}\log(S_{i,t})}{N}$, such that $s_{i,t}$ is (log) firm size normalized by the average (log) sizes computed across the N firms active in the same 2-digit sector j where firm i operates in year t.[3] Based on these average growth figures, we define, in each period, a high-growth status dummy (HG) that takes value 1 for all firms falling into the top 20% of the period-specific distribution of average growth rates, in terms of *at least* one of the two growth measures (employment or sales).

By considering both sales and employment growth in the definition of the HG group, we provide a multidimensional characterization of the growth processes of firms, accounting at the same time for different size proxies employed in the literature and reflecting the idea that no single "best" indicator of size exists. The multidimensional perspective was already pointed out in Delmar et al. (2003), where HG firms are defined as those performing in the top 10% of six growth indicators, and recently re-affirmed in Daunfeldt and Halvarsson (2015) and Bianchini et al. (2017), employing a "mixed" measure of HG that, similarly to us, combines growth of employment and growth of sales. Further, our definition implicitly defines HG firms in terms of their relative growth, thus allowing for a more equal treatment of small–medium and large firms as compared to absolute growth, as in, for instance, Delmar et al. (2003), Capasso et al. (2014), and Daunfeldt et al. (2014). Moreover, by considering annualized average growth over 3 years we account for the fact that a single big jump in size in 1 year does not seem enough to characterize firms that indeed consistently outperform the others. This is fairly recognized in the literature, as mentioned. Three-year averages, as in our study, are used in Daunfeldt et al. (2014), Hölzl (2014), and Daunfeldt and Halvarsson (2015). This is consistent with the OECD definition of HG firms, which identifies as HG the firms that achieve an annualized growth rate of at least 20% during a 3-year period and have an initial size of at least ten employees. We did not apply this definition since it tends to exclude relatively smaller firms. Lastly, our choice

[3]We discard the first year, 1998, in order to have periods of the same length. The normalization implicitly removes sector-specific common trends, such as inflation and business cycle effects in sectoral demand.

of a 20% threshold is somewhat arbitrary, although comparable with other studies on other countries. We experimented with a more stringent definition taking the top 10%, but the number of firms classified as HG dropped significantly, preventing meaningful statistical comparisons with other firms.

With our definition of HG firms, given the time span available in the data, we end up with three different measurement of high-growth status for each firm over time. We exploit this three-period panel setting to estimate the following linear probability model that describes the probability to remain in the HG group over time

$$\begin{aligned}\mathrm{HG}_{i,p} &= \alpha + \beta_0 \mathrm{HG}_{i,p-1} + \beta_1 X_{i,p-1} + \beta_2 X_{i,p-1} \\ &\quad \times \mathrm{HG}_{i,p-1} + \mathrm{Controls}_{i,p-1} + \varepsilon_{i,p} \qquad (1)\end{aligned}$$

The dependent variable $\mathrm{HG}_{i,p}$ is the binary variable indicating if firm i is high growth in period p, and $\mathrm{HG}_{i,p-1}$ is the high-growth status of firm i in period $p-1$. The matrix of explanatory variables $X_{i,p-1}$ includes the proxies of structural firm characteristics and performance that we are primarily interested in, lagged by one period, while the matrix $\mathrm{Controls}_{i,p-1}$ is a set of further firm-level attributes that we consider as controls in the first place, also lagged by one period (see below for the definitions of all the regressors).

The coefficient vector β_2 on the interaction $X_{i,p-1} \times \mathrm{HG}_{i,p-1}$ is where our primary interest lies. Indeed, this measures the contribution of each lagged firm attributes in $X_{i,p-1}$ to the probability to be HG in period p for firms that were already HG in the previous period p-1. In this sense, estimates of β_2 address whether each focal firm characteristic displays an association with persistence in high-growth status, *additional* to the association between lagged firm characteristics and the probability to be in the HG group in period p estimated for the "control group" of firms that are not HG firms in period $p-1$ ($\mathrm{HG}_{p-1} = 0$). Notice that the definition of HG is already accounting for more than single-year jumps. Thus, measuring high-growth persistence as being HG over two consecutive periods effectively yields a rather long-run notion of persistence, within the limits imposed by the data. In this respect, we share the idea developed in Bianchini et al. (2017) to go beyond yearly or short-run autocorrelation of HG status or quantile auto-regressions in the top quantiles of the growth rate distribution. They however define a group of persistent high-growth firms fixed over time. In our framework, instead, we can track changes in HG status over time.

We test several specifications of Eq. 1 where the focal firm attributes in $X_{i,p-1}$ enter one at a time and altogether. Since we are not interested in obtaining fitted probabilities, we estimate all the specifications via OLS. Pooled estimators as the OLS on our linear probability model are consistent without unobserved heterogeneity even in presence of lagged dependent variables. We choose not to include firm fixed-effects primarily because the time span available is limited (three periods), beyond the fact that unobserved heterogeneity is especially troublesome to address in presence of a lagged dependent variable. Unobserved heterogeneity and other sources of omitted variables bias, we believe, should be satisfactorily absorbed by the controls, especially when we test a "full model" where all structural characteristics $X_{i,p-1}$ and their corresponding interactions with lagged high-growth status enter at the same time. We will, in fact, consider that specification as the most reliable, as compared to the "univariate" specifications. An issue remains concerning potential standard endogeneity bias, but the short panel does not allow to apply any GMM-like method. In this sense, we do not pretend to identify any causality. We could have defined HG status on a yearly basis (top 20% of growth performance in each year over 1998–2007), allowing us to exploit the entire 10 years of data in the empirical analysis. That would have left us some more flexibility to cure endogeneity via GMM-like estimators or dynamic models for discrete choice, as in Lopez-Garcia and Puente (2012) who indeed explore whether firm characteristics impact on yearly HG status (not on persistence of HG status). In these alternative empirical settings, however, the interactions between past HG status and focal firm attributes would have captured a short-run notion of persistence.[4]

[4] Another alternative sometimes suggested in the literature on persistence of economic performance (e.g., in innovation studies) would have been to define HG status on a yearly basis, and then employ duration analysis to elicit the influence of focal firm characteristics on the length of the spells of HG growth status, over 1, 2, and more years. However, as expected given the well-known erratic nature of growth processes, we verified that in our data about 95% of all yearly HG events do not last more than 3 years, and actually 65% of them last just 1 year. We thank an anonymous referee for suggesting to clarify this point.

3.3 Firm characteristics

In designing our baseline regression model in Eq. 1, we distinguish two groups of focal and control firm-level variables.

We derive from theoretical models of firm-industry dynamics the notion that productivity, innovation, profitability, investment behavior, and financial conditions allowing to access external resources represent the key dimensions of firm structural performance underlying growth dynamics. As mentioned, with the exception of Bianchini et al. (2017), these variables are not considered in the few studies addressing persistence of high-growth, while we have more evidence concerning the demographic characteristics (size, age, sector of activity) of persistent high-growth firms. This unbalanced treatment in previous studies, as well as the theoretical relevance of these dimensions, motivates us to include them in the set of focal characteristics, as potentially distinctive features of high-growth persistence.

Accordingly, the set of focal firm attributes X_{p-1} includes the following proxies. We measure productivity as labor productivity (labeled as $PROD$), taking the ratio (in logs) of real value added (at constant prices) over number of employees. We proxy for operating profitability via the return on sales (ROS), defined as gross operating margins over total output.[5] We define firm's investment intensity (INV) as the ratio of real investment to real value added, where real investment at time t is the difference of firm's real capital stock between time t and $t-1$, and the time series of real capital stock is computed via the perpetual inventory method with 9% depreciation rate developed specifically for China in Brandt et al. (2012). We use the percentage share of output due to new products introduced in each year (NEWPROD) as our proxy for innovativeness.[6] Financial conditions of firms are taken into account through two indicators: 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), and a standard measure of leverage (LEV), computed as the ratio between total debt and total assets.[7]

Since focal firm characteristics are all continuous variables, in order to input a value for each of the three sub-periods defining our regression sample, we take the within-period, firm-specific average of each variable computed over the 3 years defining each period.

Among the more demographic variables that we include in the control set $Controls$, we consider age and size of the firms, sector and geographical dummies, as well as two firm characteristics that may be of particular importance in the context of Chinese industrial development, namely whether a firm is engaged in exporting and whether it is under public (state) or private control.

Firm age (AGE) is computed using information on firm's foundation year, and we proxy for firm size (SIZE) through the (log) number of employees. As they are both continuous variables, they enter the regression models in terms of their within-period, firm-specific averages. Export and state-ownership status are recorded via binary variables that we construct for each sub-period as follows. We recover ownership type from each firm's registration capital, and define a dummy for state-ownership (STATE) that takes value one if the firm is under state-control in at least 2 years within each 3-year subperiod, and zero otherwise.[8] The export status dummy (EXP) takes value one if the firm exports in at least 1 year within each 3-year sub-period, and zero otherwise.[9] Controlling for the geographical location of each firm is particularly important, given the well-known disparities

[5] Gross margins are essentially equivalent to an EBIDTA index, taking the difference between value added and cost of labor (total wages plus social security).

[6] "New products" are defined, according to NBS, as products adopting new technology and/or new design, or products that have been significantly improved over existing ones with respect to their structure, materials and/ or process techniques. Hence, comparing with international standards in innovation surveys as defined by the Oslo manual, "new products" in our data are new to the enterprise, but not necessarily new to the market.

[7] According to Chinese accounting rule, interest expenses is a net measure, which equals gross interest expenses minus interest revenues, and can thus take negative values.

[8] There are five types of registration capital in the NBS data: state, collective, legal person, individual, Hong-Kong Macao and Taiwan, and foreign. "State-control" indicates both State-absolute-control, i.e., the State capital share is greater than or equal to 50%, and State-relative-control, i.e., State capital share is less than 50% but it is greater than the other shareholders or the relative State-controlling status is regulated by the contract.

[9] Notice that export status changes more often than ownership and this is the reason why we define the two dummies in two different ways.

Table 1 Variables name and definitions

Variable name	Definition
PROD	(log of) Real value added at constant prices over the number of employees
ROS	Gross operating profits over total output
INV	Real investment over real value added.
NEWPROD	Share of output due to new products
IE	Interest expenses over total sales
LEV	Total debt over total assets
AGE	Current year minus foundation year
SIZE	(log) Number of employees
EXP	Binary variable: 1 if the firm exports in at least 1 year over the period
STATE	Binary variable: 1 if the firm is under state-control in at least 2 years over the period

All continuous variables are taken as the average over each of the 3-year periods

in forms and stages of industrial development characterizing the different geographical areas of China. From information in the NBS data, we can include four regional dummies, corresponding to standard macro-division identified in Chinese data: east, middle, west, and north east.[10]. All the regressions also include a full set of 2-digit sectoral dummies, according to the primary sector of activity of each firm. Both regional and sectoral dummies are fixed over time in the dataset; thus, they equally remain fixed over the 3-years sub-periods defining our regression analysis.[11] Table 1 summarizes the name and the definition of all the variables.

4 Descriptive analysis

Before turning to regression analysis, we provide a basic descriptive picture about high-growth dynamics and main explanatory variables.

Table 2 shows the total number of observations, the number of HG observations and the percentage share of HG observations in each 2-digit sector, as resulting from our identification criterion, pooling over the three sub-periods. Overall, HG firms encompass 31% of the observations. Notice that this implies that sales and employment growth are correlated to some extent. Indeed, with our definition, we expect to have from 20 to 40% of HG firms in each period, where the lower bound corresponds to perfect cross-correlation between employment growth and sales growth, whereas the upper bound corresponds to zero correlation between the two growth measures.

Next, Table 3 shows transition probabilities in HG status over two consecutive 3-year periods, pooling over the three sub-periods identified in the data. This mimics the type of persistence that we capture in the regression model although here we do not condition on firm characteristics. We do observe some persistence: around 39% of the HG firms do not change their status in the next period, whereas firms that are not HG at time t have around 28% probability to become HG firms in period $t + 1$.

Turning to firm characteristics, Table 4 provides basic descriptive statistics, pooling over the three periods and by HG status within each period. Looking at the overall means (cf. columns labeled as "All"), we detect a clear trend in some of the variables. In particular, the average (log) productivity increased from 3.609 (period 1) to 4.133 (period 2), reflecting the well-known productivity growth in Chinese manufacturing over the period. Similarly, we observe a mild increase in the average innovative activity of the firms (the share of output due to new products increased from 4 to 5.6%) and also an increasing

[10] More precisely, the East region includes Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The Middle region includes Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan. The West region includes Inner Mongolia, Guangxi, Chongqiong, Sichuan, Guizhou, Yunnan, Tibet, Shannxi, Gansu, Qinghai, Ningxia, and Xinjiang. The Northeast region includes Liaoning, Jilin, and Heilongjiang.

[11] The data cannot be matched with other data sources, due to confidentiality and restricted access, so we cannot exploit other sources of information to include further region-specific or sector-specific characteristics.

Table 2 Total number of observations and observations identified as high growth (absolute number and percentage shares), overall and by 2-digit sectors

CIC	Sector	All	HG	% of HG
13	Processing of food from agricultural products	2830	927	32.8
14	Foodstuff	1537	489	31.8
15	Manuf. of beverages	1175	365	31.1
16	Manuf. of tobacco	150	38	25.3
17	Manuf. of textile	5061	1586	31.3
18	Manuf. of textile wearing apparel, footwear, and caps	3401	1160	34.1
19	Manuf. of leather, fur, feather, and related products	1675	506	30.2
20	Processing of timber, manufacture of wood, bamboo, etc.	722	252	34.9
21	Manuf. of furniture	523	170	32.5
22	Manuf. of paper and paper products	2143	650	30.3
23	Printing, reproduction of recording media	1677	396	23.6
24	Manuf. of articles for culture, education, and sport activity	1183	417	35.2
25	Processing of petroleum, coking, processing of nuclear fuel	474	145	30.6
26	Manuf. of raw chemical materials and chemical products	5602	1584	28.3
27	Manuf. of medicines	2056	576	28.0
28	Manuf. of chemical fibers	309	122	39.5
29	Manuf. of rubber	960	305	31.8
30	Manuf. of plastics	3112	998	32.1
31	Manuf. of non-metallic mineral products	6284	1882	29.9
32	Smelting and pressing of ferrous metals	1128	361	32.0
33	Smelting and pressing of non-ferrous metals	1004	325	32.4
34	Manuf. of metal products	3384	1061	31.4
35	Manuf. of general purpose machinery	5743	1716	29.9
36	Manuf. of special purpose machinery	2946	948	32.2
37	Manuf. of transport equipment	3966	1226	30.9
39	Manuf. of electrical machinery and equipment	4725	1563	33.1
40	Manuf. of communication equipment, computers, etc.	2682	948	35.3
41	Manuf. of measuring instruments and machinery for cultural activity	1212	366	30.2
42	Manuf. of artwork and other manufacturing	1300	445	34.2
	Total	68,964	21,527	31.2

share of private or mixed ownership firms (the percentage of state-controlled firms decreases over time from 20 to about 14%). The two financial indicators, IE and LEV, display decreasing patterns, suggesting a general decrease in the dependence of firms from external finance. Obviously, the average age of firms increases over time due to the balanced structure of the panel, and also size increases during the period. Also

Table 3 Transitions in-and-out high-growth status in two consecutive periods: number of observations and transition probabilities in parentheses

		Period + 1, n (%)		
		HG = 0	HG = 1	Total
Period	HG = 0	22,901 (72.1)	8860 (27.9)	31,761 (100.0)
	HG = 1	8636 (60.8)	5579 (39.2)	14,215 (100.0)
	Total	31,537 (68.6)	14,439 (31.4)	45,976 (100.0)

Table 4 Descriptive statistics

	Pool			Period 1			Period 2			Period 3		
	All	HG = 0	HG = 1	All	HG = 0	HG = 1	All	HG = 0	HG = 1	All	HG = 0	HG = 1
HG	0.312			0.308			0.310			0.318		
	(0.463)			(0.462)			(0.463)			(0.466)		
PROD	3.863	3.753	4.106	3.609	3.526	3.796	3.848	3.752	4.063	4.133	3.986	4.449
	(0.966)	(0.939)	(0.979)	(0.922)	(0.902)	(0.938)	(0.932)	(0.918)	(0.926)	(0.971)	(0.940)	(0.961)
ROS	0.190	0.184	0.203	0.186	0.182	0.197	0.194	0.188	0.208	0.190	0.183	0.205
	(0.395)	(0.258)	(0.595)	(0.122)	(0.119)	(0.127)	(0.343)	(0.406)	(0.109)	(0.580)	(0.141)	(1.007)
INV	−0.035	−0.080	0.066	0.014	−0.049	0.156	−0.068	−0.075	−0.053	−0.050	−0.118	0.096
	(5.767)	(2.491)	(9.636)	(2.089)	(2.391)	(1.139)	(9.446)	(2.329)	(16.607)	(2.484)	(2.738)	(1.815)
NEWPROD	0.046	0.046	0.047	0.040	0.041	0.037	0.044	0.045	0.042	0.056	0.053	0.063
	(0.144)	(0.142)	(0.148)	(0.133)	(0.133)	(0.133)	(0.139)	(0.140)	(0.138)	(0.158)	(0.153)	(0.169)
IE	0.014	0.015	0.012	0.019	0.021	0.015	0.013	0.014	0.011	0.011	0.011	0.009
	(0.026)	(0.025)	(0.027)	(0.033)	(0.031)	(0.035)	(0.024)	(0.022)	(0.027)	(0.019)	(0.020)	(0.016)
LEV	0.580	0.584	0.571	0.589	0.593	0.580	0.579	0.582	0.570	0.572	0.577	0.562
	(0.256)	(0.263)	(0.238)	(0.244)	(0.248)	(0.235)	(0.256)	(0.265)	(0.233)	(0.267)	(0.276)	(0.246)
AGE	18	19	15	15	17	10	18	19	14	21	21	19
	(14)	(15)	(12)	(14)	(15)	(10)	(14)	(15)	(11)	(14)	(15)	(12)
SIZE	533	529	543	516	561	417	527	518	547	555	506	660
	(1874)	(1933)	(1737)	(1951)	(2205)	(1194)	(1718)	(1842)	(1406)	(1943)	(1716)	(2354)
EXP	0.470	0.454	0.504	0.472	0.452	0.515	0.451	0.436	0.485	0.486	0.474	0.512
	(0.499)	(0.498)	(0.500)	(0.499)	(0.498)	(0.500)	(0.498)	(0.496)	(0.500)	(0.500)	(0.499)	(0.500)
STATE	0.172	0.199	0.111	0.200	0.236	0.120	0.173	0.202	0.109	0.142	0.160	0.104
	(0.377)	(0.399)	(0.314)	(0.400)	(0.424)	(0.325)	(0.378)	(0.401)	(0.312)	(0.349)	(0.366)	(0.305)

Mean and standard deviations (in parenthesis) of the following variables: high-growth status dummy (HG), taking value one if firm is high-growth according to our definition; productivity (PROD) computed as the log of value added over number of employees; return on sales (ROS), computed as gross operating margins over output; investment intensity (INV), computed as real investment over real value added; share of output due to new products (NEWPROD); the ratio of interest expenses to sales (IE); firm leverage (LEV) computed as the ratio of total debt over total assets; firm age is computed from year of foundation (AGE); number of employees (SIZE); a dummy variable for firms' export status (EXP); and a dummy variable indicating state-control status (STATE)

Table 5 Two-sample Fligner-Policello robust rank order test

	Number of Obs.									
Period	HG = 0	HG = 1	PROD	ROS	INV	NEWPROD	IE	LEV	EMP	AGE
Pool	47,394	21,570	−46.18**	−25.80**	−79.67**	0.30	14.98**	5.90**	−4.32**	42.33**
1999–2001	15,909	7079	−21.18**	−9.88**	−43.45**	3.71**	15.30**	4.18**	8.65**	40.26**
2002–2004	15,818	7170	−24.65**	−12.01**	−46.91**	1.44	9.00**	2.33	−5.55**	25.91**
2005–2007	15,667	7321	−36.78**	−22.65**	−49.22**	−4.37**	0.73	3.49**	−10.30**	11.68**

FP statistics and observations are reported. Non-HG firms as the benchmark group: a positive and significant FP statistic means that non-HG firms dominate; a negative and significant FP statistic means that HG firms dominate. Asterisks denote significance levels (*$p<1\%$; **$p<0.1\%$)

notice that almost half of the firms in our sample are exporters, as we define them, and about 17–20% are state-controlled.

Comparing HG firms with other firms (cf. columns labeled as HG = 1 vs. HG = 0) reveals other interesting features of the sample. On average, across the three periods, HG firms display higher labor productivity, higher profitability, higher investment intensity, lower interest expenses as a percentage of sales, and lower leverage. HG firms are also younger, but larger in terms of employment (except for period 1). Less marked differences are observed concerning the innovative activity, with the group of other firms performing slightly better in terms of product innovation in periods 1 and 2. Finally, we observe a lower share of state-controlled firms and a higher share of exporters within the HG group. The standard deviations in Table 4 also reveal wide and persistent heterogeneities in all the dimensions of firms' "identity cards," confirming the well-known stylized fact that most variables do exhibit high degrees of skewness.[12] In this sense, average values may provide a poor reference for comparisons, whereas distributional comparisons are more revealing. Accordingly, we also performed a formal Fligner and Policello (1981) test of distributional equality, between the distribution of each variable across HG and other firms.

Table 5 reports the results. We take the group of non-HG firms as the reference category, so that a positive and statistically significant FP statistic indicates that non-HG firms dominates HG firms with respect to the considered firm attribute, while HG firms dominate over other firms when the FP statistic is negative and significant. The tests confirm the conclusion drawn from the comparison of simple averages. In particular, HG firms dominate in terms of productivity, profitability, investment intensity, and size, as compared to other firms. Conversely, HG firms do not dominate in terms of interest expenses, leverage, and age. Overall, we confirm findings in the literature that high-growth firms tend to display more solid characteristics, beyond being relatively younger, larger, more often exporters and more concentrated in non-state-controlled companies. Results on the share of sales due to product innovation are less clear-cut: HG firms tend to outperform other firms only in the last sub-period.

5 Main results

High-growth firms appear to differ from other firms. Yet, do firm characteristics stand also out as distinguishing features of high-growth persistence? In this section, we present the main estimates of our baseline regression framework, eliciting the role of our focal firm attributes in the ability to replicate high-growth over time. In the next section, we will devote specific focus to dissecting the role of age, size, ownership-type.

The results are shown in Table 6. We start presenting the univariate specifications where each firm characteristic is included at a time, together with its interaction with lagged HG status (in columns 1–6). We find that productivity is associated with an increased probability of high-growth status, and the association is even larger for firms that remain

[12] This is confirmed by looking at kernel densities of all variables, for both HG and other firms. Results are not reported, but available upon request.

Table 6 Main estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
HG_{p-1}	0.0339	0.0568***	0.0931***	0.0934***	0.0959***	0.1069***	0.0518*
	(0.0202)	(0.0096)	(0.0049)	(0.0051)	(0.0054)	(0.0125)	(0.0257)
$PROD_{p-1}$	0.0326***						0.0361***
	(0.0030)						(0.0032)
$PROD_{p-1} \times HG_{p-1}$	0.0132*						0.0115
	(0.0052)						(0.0061)
ROS_{p-1}		0.0022					−0.0193**
		(0.0183)					(0.0066)
$ROS_{p-1} \times HG_{p-1}$		0.1785***					−0.0047
		(0.0415)					(0.0429)
INV_{p-1}			−0.0012				−0.0004
			(0.0012)				(0.0013)
$INV_{p-1} \times HG_{p-1}$			0.0014				0.0006
			(0.0012)				(0.0013)
$NEWPROD_{p-1}$				0.0619**			0.0257
				(0.0193)			(0.0193)
$NEWPROD_{p-1} \times HG_{p-1}$				−0.0120			−0.0161
				(0.0355)			(0.0357)
IE_{p-1}					0.3228**		0.4763***
					(0.0999)		(0.1109)
$IE_{p-1} \times HG_{p-1}$					−0.1552		−0.1891
					(0.1662)		(0.1859)
LEV_{p-1}						−0.0066	0.0015
						(0.0098)	(0.0106)
$LEV_{p-1} \times HG_{p-1}$						−0.0238	−0.0109
						(0.0199)	(0.0209)
AGE_{p-1}	−0.0017***	−0.0020***	−0.0021***	−0.0021***	−0.0021***	−0.0020***	−0.0018***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$SIZE_{p-1}$	−0.0332***	−0.0372***	−0.0374***	−0.0383***	−0.0380***	−0.0374***	−0.0340***
	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0023)
EXP_{p-1}	0.0171***	0.0214***	0.0203***	0.0188***	0.0210***	0.0197***	0.0167***
	(0.0050)	(0.0050)	(0.0050)	(0.0050)	(0.0050)	(0.0050)	(0.0051)
$STATE_{p-1}$	−0.0512***	−0.0516***	−0.0521***	−0.0542***	−0.0534***	−0.0518***	−0.0543***
	(0.0059)	(0.0059)	(0.0059)	(0.0060)	(0.0059)	(0.0059)	(0.0059)
Constant	0.3433***	0.5041***	0.5062***	0.5114***	0.5055***	0.5100***	0.3309***
	(0.0204)	(0.0155)	(0.0150)	(0.0151)	(0.0150)	(0.0160)	(0.0223)
Observations	45,976	45,976	45,976	45,976	45,976	45,976	45,976
R^2	0.0416	0.0375	0.0369	0.0372	0.0372	0.0370	0.0424

Linear probability (OLS) estimates of Eq. 1. All specifications include sector (2-digit) and region fixed-effects. Robust standard errors in parentheses: asterisks denote significance levels (***$p<0.1\%$; **$p<1\%$; *$p<5\%$)

high growth in two consecutive periods (column 1). Profitability alone does not play statistically significant role in explaining high growth of non-persistent high-growth firms, but it is positively associated with the persistence of high-growth (column 2). Firm's product innovation increases the probability that a non-HG firm becomes HG, but there is no additional contribution of product innovation to the persistence into the HG status (column 4). The same holds concerning interest expenses over sales (column 5). Finally, investment intensity and leverage do not display any statistically significant association neither with HG status nor with persistence of HG status (columns 3 and 6). Also notice that the coefficients on the control variables are strongly significant in all the specifications. Younger and smaller firms tend to have more chances to be high growth, and the same holds for exporters and firms that are not under direct state-control.

We next move (in column 7) to the estimates of the "full model." The results convey a remarkably different picture, especially regarding the relevance of firms characteristics for high-growth persistence. We confirm that lagged productivity and interest expenses (over sales) stand out as key features that distinguish firms that switch from non-HG to HG status over time, while at the same time, HG firms suffer from comparatively lower profitability. However, and more interestingly, none of the key structural firm characteristics displays a statistically significant association with the ability to persistently remain in the HG group. Indeed, the estimated interaction coefficients are all statistically equal to zero.

6 Dissecting the role of age, size, and state-ownership

The analyses of the previous section suggest that persistently high-growing firms do not seem to differ from "simple" high-growth firms along standard proxies of industrial and structural performance. A major question remains, pertaining to the role of demographic characteristics. Starting at least from the seminal work of Birch (1981), small-medium firms have been considered, especially by policy makers, as the main candidates to become "gazelles." More recent contributions, however, have shown that age, rather than size, may be the key driver of high-growth performance. In particular, Haltiwanger et al. (2013), using data from the Census Bureau's Longitudinal Business Database (LBD), show that the negative relationship between firm size and growth disappears, and it may even reverse its sign among large firms, once one accounts for the age dimension (see also Lawless (2014) on Irish firms and Grazzi and Moschella (2017) on Italian firms). Decker et al. (2016) provide further evidence on young high-growth firms in the USA). On top of age and size, the specific context of the Chinese economy suggests to also consider the distinction between state vs. private ownership as a further dimension that can be crucial to identify the surces of high-growth and high-growth persistence.

In this section, we explore whether persistence of high growth itself depends on age, size, and ownership type, and we ask if the relations between more structural firm characteristics and persistence of high-growth display specific patterns across firms of different age, size, and ownership type.

6.1 Young vs. old firms

Table 7 presents the estimates of a series of variations of our baseline regression in Eq. 1, where we explore the role of firm age. In column 1, we add an explicit interaction between lagged HG status and age. Next, we split the sample according to age, defining each firm as young if she is less than 10 years old in the last year of the sample (2007), and as an old firm otherwise.[13] Young firms account for 3.48% of total observations, and we exploit the splitting by age in two ways. In column 2, we interact lagged HG status with a dummy identifying young firms, while in columns 3 and 4, we report results of separate estimates of Eq. 1 on the two groups of young and old firms.

All the specifications convey a consistent picture. On the one hand, we confirm that HG firms tend to be younger than non-HG firms (negative coefficient on AGE and positive on the young-firm dummy), but age does not emerge as a distinguishing feature of persistent high-growth firms (the interactions of age with lagged HG status are not significant). On the other hand, the coefficient estimated on the other firm attributes broadly replicate the baseline patterns reported in Table 6. In particular, none of the focal structural firm characteristics displays systematic relations with high-growth persistence, neither within young nor within old firms.

6.2 Small, medium, and large firms

In Table 8, we perform a similar analysis focusing on firm size. We first add an interaction between lagged size (as number of employees) and lagged HG status (in column 1). Next, we explore the relevance of different splits of the sample that identify small vs. medium–large firms, and small–medium vs. large enterprises. We exploit two "official" definitions employed by Chinese authorities: small firms are defined as having less than 300 employees, while small–medium firms are defined as employing less than 1000 employees.[14] Dummy variables

[13]Notice that, given the data span 10 years, young firms include only firms entering the sample exactly during the years covered in the data.

[14]This size categorization method was adopted by the Chinese State Economic and Trade Commission in 2011.

Table 7 The role of firm age

	(1) All	(2) All	(3) Old	(4) Young
HG_{p-1}	0.0540*	0.0652*	0.0658*	−0.0341
	(0.0265)	(0.0257)	(0.0263)	(0.1314)
$PROD_{p-1}$	0.0362***	0.0396***	0.0394***	0.0466*
	(0.0032)	(0.0032)	(0.0032)	(0.0227)
$PROD_{p-1} \times HG_{p-1}$	0.0112	0.0096	0.0093	0.0118
	(0.0062)	(0.0061)	(0.0063)	(0.0303)
ROS_{p-1}	−0.0194**	−0.0192**	−0.0191**	−0.0384
	(0.0066)	(0.0068)	(0.0069)	(0.1993)
$ROS_{p-1} \times HG_{p-1}$	−0.0035	−0.0091	−0.0031	−0.0631
	(0.0431)	(0.0429)	(0.0439)	(0.2817)
INV_{p-1}	−0.0004	−0.0003	−0.0002	−0.0006
	(0.0013)	(0.0013)	(0.0014)	(0.0063)
$INV_{p-1} \times HG_{p-1}$	0.0006	0.0004	0.0004	0.0093
	(0.0013)	(0.0013)	(0.0014)	(0.0239)
$NEWPROD_{p-1}$	0.0253	0.0133	0.0141	−0.0645
	(0.0194)	(0.0193)	(0.0196)	(0.1237)
$NEWPROD_{p-1} \times HG_{p-1}$	−0.0144	−0.0091	0.0135	−0.3109*
	(0.0360)	(0.0356)	(0.0366)	(0.1572)
IE_{p-1}	0.4750***	0.4766***	0.4715***	0.6030
	(0.1109)	(0.1098)	(0.1108)	(0.7343)
$IE_{p-1} \times HG_{p-1}$	−0.1864	−0.1838	−0.2107	1.2155
	(0.1864)	(0.1855)	(0.1853)	(1.2837)
LEV_{p-1}	0.0013	−0.0087	−0.0061	−0.1321
	(0.0106)	(0.0105)	(0.0106)	(0.0778)
$LEV_{p-1} \times HG_{p-1}$	−0.0099	−0.0091	−0.0108	0.0911
	(0.0211)	(0.0210)	(0.0214)	(0.1132)
AGE_{p-1}	−0.0018***			
	(0.0002)			
$AGE_{p-1} \times HG_{p-1}$	−0.0001			
	(0.0004)			
YOUNG		0.0423**		
		(0.0164)		
$YOUNG \times HG_{p-1}$		−0.0255		
		(0.0244)		
$SIZE_{p-1}$	−0.0340***	−0.0388***	−0.0386***	−0.0408**
	(0.0023)	(0.0022)	(0.0023)	(0.0129)
EXP_{p-1}	0.0166**	0.0205***	0.0191***	0.0503
	(0.0051)	(0.0051)	(0.0051)	(0.0280)
$STATE_{p-1}$	−0.0543***	−0.0720***	−0.0731***	−0.0524
	(0.0059)	(0.0057)	(0.0057)	(0.0395)
Constant	0.3303***	0.3208***	0.3240***	0.3371**
	(0.0223)	(0.0223)	(0.0227)	(0.1272)
Observations	45,976	45,976	44,374	1602
R^2	0.0424	0.0405	0.0403	0.0628

Linear probability (OLS) estimates of Eq. 1 adding an interaction of HG_{p-1} with lagged age (column 1) or with a dummy for lagged young firm status (column 2), and split sample analysis by old and young firms (columns 3 and 4). All specifications include sector (2-digit) and region fixed-effects. Robust standard errors in parentheses: asterisks denote significance levels (***$p<0.1\%$; **$p<1\%$; *$p<5\%$)

for small and small–medium firms are added, both alone and interacted with lagged HG status in column 2 and column 5, respectively, while split sample analysis by size groups is reported in columns 3–4 (small vs medium–large firms) and in columns 6–7 (small–medium vs. large firms). To avoid simultaneity

Table 8 Analysis by firm size

Regressors	(1) All	(2) All	(3) Medium–large	(4) Small	(5) All	(6) Large	(7) SMEs
HG_{p-1}	0.0399	0.0364	0.0104	0.0692*	0.0549	0.1406	0.0385
	(0.0395)	(0.0261)	(0.0445)	(0.0325)	(0.0308)	(0.0912)	(0.0271)
$PROD_{p-1}$	0.0360***	0.0391***	0.0275***	0.0508***	0.0413***	0.0294***	0.0443***
	(0.0032)	(0.0032)	(0.0048)	(0.0052)	(0.0032)	(0.0088)	(0.0042)
$PROD_{p-1} \times HG_{p-1}$	0.0120	0.0140*	0.0101	0.0076	0.0136*	−0.0080	0.0121
	(0.0063)	(0.0062)	(0.0112)	(0.0080)	(0.0061)	(0.0224)	(0.0068)
ROS	−0.0194**	−0.0196**	−0.0203**	−0.0640	−0.0204**	−0.0193	−0.0475
	(0.0066)	(0.0070)	(0.0077)	(0.0392)	(0.0072)	(0.0120)	(0.0300)
$ROS \times HG_{p-1}$	−0.0053	−0.0192	0.1055	−0.0293	−0.0208	0.2884	−0.0167
	(0.0430)	(0.0433)	(0.0766)	(0.0628)	(0.0434)	(0.1664)	(0.0523)
INV_{p-1}	−0.0004	−0.0007	0.0003	−0.0019	−0.0007	0.0002	−0.0016
	(0.0013)	(0.0013)	(0.0016)	(0.0016)	(0.0013)	(0.0026)	(0.0014)
$INV4_{p-1} \times HG_{p-1}$	0.0006	0.0009	0.0094	0.0020	0.0009	0.0066	0.0017
	(0.0013)	(0.0013)	(0.0053)	(0.0016)	(0.0013)	(0.0039)	(0.0014)
$NEWPROD_{p-1}$	0.0266	0.0069	−0.0084	0.0373	0.0035	0.0350	−0.0079
	(0.0194)	(0.0193)	(0.0247)	(0.0316)	(0.0194)	(0.0397)	(0.0226)
$NEWPROD_{p-1} \times HG_{p-1}$	−0.0187	-0.0128	0.0061	−0.0402	−0.0162	−0.0154	−0.0105
	(0.0363)	(0.0361)	(0.0542)	(0.0507)	(0.0362)	(0.0875)	(0.0403)
IE_{p-1}	0.4778***	0.4456***	0.4935**	0.3814*	0.4132***	0.3056	0.4299***
	(0.1110)	(0.1112)	(0.1546)	(0.1628)	(0.1101)	(0.2379)	(0.1197)
$IE_{p-1} \times HG_{p-1}$	−0.1905	-0.1478	−0.3314	−0.0560	−0.1232	0.6768	−0.1615
	(0.1859)	(0.1854)	(0.3553)	(0.2341)	(0.1845)	(0.7740)	(0.1923)
LEV_{p-1}	0.0014	0.0045	−0.0101	0.0143	0.0055	0.0285	0.0028
	(0.0106)	(0.0106)	(0.0163)	(0.0138)	(0.0106)	(0.0304)	(0.0113)
$LEV_{p-1} \times HG_{p-1}$	−0.0108	−0.0110	0.0259	−0.0286	−0.0127	−0.1218	−0.0045
	(0.0209)	(0.0210)	(0.0385)	(0.0252)	(0.0209)	(0.0812)	(0.0218)
$SIZE_{p-1}$	−0.0346***						
	(0.0026)						
$SIZE_{p-1} \times HG_{p-1}$	0.0019						
	(0.0046)						
SMALL		0.0457***					
		(0.0056)					
$SMALL \times HG_{p-1}$		−0.0004					
		(0.0106)					
SMEs					0.0332***		
					(0.0079)		
$SMEs \times HG_{P-1}$					−0.0145		
					(0.0185)		
AGE_{p-1}	−0.0018***	−0.0020***	−0.0016***	−0.0025***	−0.0023***	−0.0010**	−0.0027***
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0004)	(0.0002)
EXP_{p-1}	0.0167***	0.0035	−0.0044	0.0060	−0.0018	−0.0105	−0.0026
	(0.0051)	(0.0049)	(0.0079)	(0.0063)	(0.0049)	(0.0148)	(0.0052)
$STATE_{p-1}$	−0.0541***	−0.0607***	−0.0731***	−0.0523***	−0.0637***	−0.0585***	−0.0669***
	(0.0060)	(0.0059)	(0.0082)	(0.0088)	(0.0060)	(0.0162)	(0.0065)

Table 8 (continued)

Regressors	(1) All	(2) All	(3) Medium–large	(4) Small	(5) All	(6) Large	(7) SMEs
Constant	0.3345***	0.1260***	0.1963***	0.1227***	0.1257***	0.1512*	0.1589***
	(0.0236)	(0.0195)	(0.0305)	(0.0256)	(0.0209)	(0.0629)	(0.0207)
Observations	45,976	45,976	16,668	29,308	45,976	4542	41,434
R^2	0.0424	0.0395	0.0352	0.0310	0.0380	0.0413	0.0356

Linear probability (OLS) estimates of Eq. 1 exploring the role of firm size (as number of employees). In column 1, we add an interaction $\mathrm{SIZE}_{p-1} \times \mathrm{HG}_{p-1}$; in column 2, we add an interaction between HG_{p-1} and a dummy for lagged small firm status (less than 300 employees); in columns 3 and 4, we split the sample between small vs medium–large (more than 300 employees) firms; in column 5, we add an interaction between HG_{p-1} and lagged small–medium firm status (less than 1000 employees); in columns 6 and 7, we split the sample between small–medium vs large (more than 1000 employees) firms. All specifications include sector (2-digit) and region fixed-effects. Robust standard errors in parentheses: asterisks denote significance levels (***$p<0.1\%$; **$p<1\%$; *$p<5\%$)

between growth patterns and the definition of the size groups, we consider the number of employees in the initial year of the sample (1998). Small firms account for 63.75% of the observations in our balanced panel, while 90.12% of the sample falls into the small–medium size category.

The results are quite invariant across the different specifications and the different definitions of size groups. We confirm our baseline result that HG firms are generally smaller in size than other firms, but firm size does not play any role in the degree of persistence of high-growth performance, no matter if we take small or small–medium firms as the reference size category. Finally, and much in line with what observed when splitting by age, we once again observe that firm attributes in general do not associate with persistence of high-growth, apart from very small and barely significant coefficients on the size-productivity interaction.

6.3 State-controlled vs. non-state-controlled firms

Finally, in Table 9, we explore whether there is a relation between high-growth persistence and ownership-type. In column 1, we add an interaction between the (lagged) dummy STATE for state-controlled firms and (lagged) HG status. Next, in columns 2 and 3, we report split-sample estimates of the baseline regression model performed separately on the two groups of state-controlled vs. non-state-controlled firms.

Two remarkable findings emerge. First, non-state-controlled firms are more likely to become HG, but ownership type does not affect persistence of HG status (see column 1). Second, we once again obtain that structural characteristics do not show systematic relations with the ability to replicate high-growth events over time. Productivity does, although only in one single specification (see the interaction coefficient in column 3).

7 Final remarks

While a large literature studies the characteristics of high-growth firms, and the conditions that can ease their birth and development, in this paper, we ask the perhaps more crucial question concerning the characteristics that associate with the ability to achieve high-growth *persistently* over time. From a policy perspective, persistent high-growth firms turn more attractive than "simple" high-growth firms, since more substantive and long-lasting gains for the economy are to be expected from firms that consistently outperform over time.

Notwithstanding its relevance, persistence of high-growth receives little and only very recent attention in the empirical literature. From the few existing studies, mostly based on developed countries, we know that persistently high-growing firms represent a small subset of the industrial sector and are usually small in size and young. The dynamism of the Chinese economy during the miracle of the 2000s, sustained by the Chinese authorities through promotion of entrepreneurship and private business, provides an interesting test bed for the identification of the characteristics that distinguish persistently high-growth firms.

Our main finding, however, is that structural characteristics do not display any systematic association with the probability to replicate high-growth over time. The result challenges most theories of

Table 9 Analysis by ownership type

Regressors	(1) All	(2) Non-state-control	(3) State-control
HG_{p-1}	0.0552*	0.0727**	−0.0646
	(0.0258)	(0.0280)	(0.0687)
$PROD_{p-1}$	0.0365***	0.0407***	0.0218**
	(0.0032)	(0.0045)	(0.0069)
$PROD_{p-1} \times HG_{p-1}$	0.0111	0.0040	0.0411**
	(0.0061)	(0.0071)	(0.0154)
ROS_{p-1}	−0.0198**	−0.0270	−0.0049
	(0.0067)	(0.0344)	(0.0065)
$ROS_{p-1} \times HG_{p-1}$	−0.0043	0.0235	−0.0956
	(0.0431)	(0.0574)	(0.0824)
INV_{p-1}	−0.0003	0.0021	−0.0029*
	(0.0013)	(0.0015)	(0.0014)
$INV_{p-1} \times HG_{p-1}$	0.0005	−0.0019	0.0157
	(0.0013)	(0.0015)	(0.0081)
$NEWPROD_{p-1}$	0.0222	0.0111	0.0648*
	(0.0194)	(0.0245)	(0.0327)
$NEWPROD_{p-1} \times HG_{p-1}$	−0.0075	0.0172	−0.0872
	(0.0361)	(0.0427)	(0.0693)
IE_{p-1}	0.4573***	0.5061***	0.3114
	(0.1104)	(0.1316)	(0.1784)
$IE_{p-1} \times HG_{p-1}$	−0.1548	−0.2365	0.0794
	(0.1876)	(0.2188)	(0.2840)
LEV_{p-1}	0.0002	−0.0038	0.0224
	(0.0106)	(0.0121)	(0.0216)
$LEV_{p-1} \times HG_{p-1}$	−0.0105	−0.0070	−0.0002
	(0.0209)	(0.0229)	(0.0539)
$STATE_{p-1}$	−0.0480***		
	(0.0066)		
$STATE_{p-1} \times HG_{p-1}$	−0.0278		
	(0.0146)		
AGE_{p-1}	−0.0019***	−0.0024***	−0.0009***
	(0.0002)	(0.0002)	(0.0003)
$SIZE_{p-1}$	−0.0343***	−0.0355***	−0.0334***
	(0.0023)	(0.0027)	(0.0048)
EXP_{p-1}	0.0170***	0.0162**	0.0071
	(0.0051)	(0.0056)	(0.0117)
Constant	0.3295***	0.3208***	0.3444***
	(0.0223)	(0.0263)	(0.0466)
Observations	45,976	38,736	7240
R^2	0.0423	0.0344	0.0440

Linear probability (OLS) estimates of Eq. 1 adding an interaction of HG_{p-1} with a dummy for lagged state-control status (column 1), and split sample analysis by firms under non-state and state control (columns 2 and 3). All specifications include sector (2-digit) and region fixed-effects. Robust standard errors in parentheses: asterisks denote significance levels (***$p<0.1\%$; **$p<1\%$; *$p<5\%$)

firm-industry dynamics sharing the notion that idiosyncratic specificities of firms are the key drivers of comparative advantages, leading to sustained growth over time. Rather, our findings may be interpreted as more in line with theories that conceptualize firm growth as a random process essentially guided by luck.

The implications of our findings are perhaps not good news for policy makers. Our analysis indeed speaks against the large benefits usually attributed to the emergence and development of high-growth firms. Since those few firms that display a systematic ability to persistently achieve high-growth do not differ from other firms along any of the dimensions of industrial and financial performance considered by us, it is not to be expected that they contribute to improving the overall performance of the economy over the medium- and long-run. Policy measures sustaining high-growth firms may be doomed to only exert short-term effects on the economy.

To some extent, the findings are surprising in view of the spectacular growth achieved in China during the period under study. Intuitively, we would have expected that, first, more firms were able to achieve persistent high-growth compared to the relatively low number we observe here and, second, that such firms were indeed bringing a positive contribution to the economy, especially in terms of efficiency, profits, and balanced financial structures. Conversely, we essentially replicate the conclusions drawn by Bianchini et al. (2017) from their analysis of European firms. This similarity of findings across countries suggests that our results may not be peculiar to the Chinese context. We may have set the initial emergence of a stylized empirical regularity suggesting that something more than structural characteristics drives high-growth persistence over time, independently from country and time periods analysed.

Needless to say, a number of additional analysis could be envisaged to further corroborate our conclusions. This work provides strong evidence that there are no statistically significant differences across persistent high-growth firms and other firms, whereas we do not claim any causal interpretation. Relatedly, a promising avenue for further research would be to undertake systematic analysis of long-run high-growth performance of firms receiving policy support, while we cannot conduct a direct policy evaluation exercise in this study. Moreover, beyond the obvious need to validate our results on other countries, institutional contexts, and time periods, 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. At the same time, although we stress the need to consider a long-run notion of high-growth persistence, beyond the usual focus on single-year or very short-run spurts of high growth, the understanding of persistent high-growth dynamics would greatly benefit from the availability of longer-in-time datasets.

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