One swallow does not make a summer: Episodes and persistence in high-growth

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Abstract

This paper analyzes the episodes (spells) of high-growth in firm size and tracks their length in a sample of Spanish manufacturing firms observed over about two decades. The use of duration models allows us (i) to take a year-on-year perspective in the analysis of episodes and persistence in high-growth, (ii) to study the determinants of the transitions *to* and *from* the high-growth state, and (iii) to check if these factors change their role across the business cycle. While about half of the firms experience at least one episode of high-growth, these do not show a higher probability to repeat it in the subsequent years. Moreover, just a few spells of high-growth last for multiple years (persistence is rare), but these show a probability of lasting longer as their length increases. These two results point out the "episodic" nature of the high-growth phenomenon. Additionally, several firm and market (demand) characteristics matter in rising the probability of starting a high-growth spell and, to a lesser extent, to make the spell lasting longer. Finally, during downturn, the role of younger age and smaller size in explaining high-growth decreases.

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1. Introduction

In the last decades, an increasing attention has been paid to that small group of firms that are able to expand their size at a very fast pace.[1] These businesses, usually referred to as high-growth firms (HGFs), have attracted the interest of policy makers (Vértesy et al., 2017), academic scholars (Henrekson and Johansson, 2010) and the popular press (The Economist, 2012), because they are responsible for the creation of most new jobs across countries and industries (Schreyer, 2000; Nesta, 2009; Audretsch, 2012; Haltiwanger et al., 2017).

Yet, some aspects of the HGFs remain less clear-cut (Coad et al., 2014). First, except for few demographic characteristics of the firm, such as younger age and smaller size, it is hard to define a set of consistent determinants of HGFs that hold across industrial sectors and over time (Coad et al., 2014; World Bank, 2019). In particular, the evidence of the behavior of HGFs over the different phases of the business cycle is scant. Second, and very much connected with the first issue, it is difficult to recognize patterns of high-growth: one the one hand, it is difficult to point out what makes a high-growth episode to last longer and, on the other hand, it is hard for firms to repeat a high-growth episode (HGE) over succeeding years (Hölzl, 2014; Daunfeldt and Halvarsson, 2015). The combination of these two issues has relevant implications. Indeed, one may question if it is effective at all to outline policies aimed at (*ex-ante*) targeting potential HGFs, or if it may be more efficient to foster a proper economic environment in which as many episodes of high-growth as possible occur across all the active firms (Coad et al., 2014; World Bank, 2019).

In this work, we investigate these aspects of the high-growth phenomenon in a sample of Spanish manufacturing firms with more than 10 employees observed in the period 1991-2015. After having spotted the episodes (spells)[2] of high-growth (HG) and non-high-growth (NHG, which include both low and negative yearly growth episodes), together with the transitions that occur, as years pass, between these two status, we use multi-spell discrete time duration functions to model the transitions from NHG to HG, as well as the transitions from HG to NHG. We rely on duration analysis for several reasons. First, it focuses on the timing of transitions of HG and NHG (i.e., when they take place) and not just on whether they occurred. Hence, it matters the timing of the transition as well as time between transitions, that is, survival in a particular state (e.g. length of HG spells). Second, these methods allow capturing the existence of duration dependence. That is, to check that persistence in a state is related to previous experience in that state. Third, along with transitions between NHG and HG states, other characteristics of the firms may also change over time. In order to inquire into the

[1] Empirical papers have shown that the distribution of firm growth rates may well be approximated by a Laplace distribution (see Bottazzi and Secchi, 2006; Bottazzi et al. 2011; among others). Its "heavy" tails reveal the existence of a reduced group of episodes of fast growth (and other few ones of fast contraction).

[2] Throughout the paper, we use the words *spell* and *episode* as interchangeable.

determinants of the two types of transition, we include in the empirical model a large vector of spell, firm and market characteristics and we explicitly interact them with the different phases of the business cycle. Fourth, it is uncommon to observe all HG and NHG episodes over the whole lifetime of a firm because it is dropped out from a survey, the follow-up period ends… However, the knowledge that the firm has been through HG and NHG until it leaves the sample contains valuable information. Duration models are well suited to take these issues into account. In addition, the application of duration models, which is rather new in the extant literature on HGFs (see Section 2.2.), is enhanced by the use of a panel of firms observed during more than two decades. This time-span allows us to observe a large number of HGEs along both the expansionary and contractionary phases of the recent business cycle in Spain.

The main results follow. First, while about half of the firms in the sample experience at least one episode (spell) of HG, persistence in HG on a year-on-year basis is difficult (about 75% of HG spells in the sample last 1 year only). Indeed, on average, HG spells are much shorter than NHG spells. In other words, while experiencing an episode of HG is not so uncommon for the firms in the sample, it is very likely that this will be "short". Second, some characteristics of the spells point the "episodic" nature of high-growth. Indeed, firms that experience one episode of HG do not show a higher probability of experiencing it again in the subsequent years; conversely, a reduced number of spells of HG last for multiple (3 or more) years and show a probability of lasting longer, as their length increases (negative duration dependence). These results are, in our view, coherent with the idea that multiple and long spells of HG are hard to occur within the same firm, and that the "episodic" nature of HG should be better taken into account by both scholars and policy makers (World Bank, 2019). Third, firm characteristics still matter. Indeed, smaller size, younger age, higher productivity and the introduction of new processes are all relevant in rising the probability of starting a HG spell (departing from the state of NHG) and, to a lesser extent, to experience a longer spell of HG. Fourth, market characteristics (demand) also play a relevant role, being the expansion of the market in which a firm is active and an increasing firm's market share positively associated with the probability of starting a HG spell. Fifth, differences in the explanatory power of some of these variables are observable across the different phases of the business cycle (i.e. until 2007 *versus* from 2008 onwards): during downturn, the role of younger age and smaller size in explaining the starting of episodes of HG is reduced. Sixth, a complementary analysis on the length and repetition of HG spells reaffirm the relevant role (further than age and size) played by market dynamism and process innovation strategies, while suggesting the difficulties in explaining the (scarce) repetition of HG spells within firms.

This work contributes to the modern literature on industrial dynamics in a number of respects. While the literature is vast on HGFs (see Schreyer, 2000; Delmar et al. 2003; Acs and Mueller, 2008; Haltiwanger et al., 2017; among others) and on the persistence in firm growth (see Coad, 2007b; Coad and Hölzl, 2009; Coad et al. 2018, among others), fewer contributions on the persistence in HG (Hölzl, 2014; Daunfeldt and Halvarsson, 2015; Bianchini and Pellegrino, 2019) and its determinants (Bianchini et al., 2017) have led to mixed results. We employ duration models to track the spells of specific growth states (either HG or NHG) and to identify the transitions between the two states, without imposing (as it is common in the extant literature on HGFs) any particular "structure" to persistence in firm growth, such as a certain number of lags in the autocorrelation coefficient of growth rates. We model the two types of transitions as functions of a vector of spell, firm and market characteristics. Indeed, while the transition from HG to NHG is relevant *per se*, as a proper way to study persistence in HG, the two types of transitions may be explained by different set of factors. Furthermore, the few studies inquiring into the persistence in HG have been able to track firm growth over a decade at most (see Daunfeldt and Halvarsson, 2015; Bianchini et al., 2017; Moschella et al. 2019, among others). This fact has prevented them from exploiting the different phases of the business cycle as possible enhancers or moderators of the determinants of high-growth and the persistence in it. We, instead, are able to exploit them and we appreciate some significant differences over the cycle. Finally, we contribute to the literature on the growth of modern economies, which is linked to their ability of generating "dynamic businesses". This dynamism plays a relevant role not just in terms of job creation (Criscuolo et al., 2014; Coad et al. 2014), but also in terms of resource re-allocation across firms, which is key for productivity growth (Bravo-Biosca, 2011; Haltiwanger et al., 2017) and innovation (Acemoglu et al., 2018). In this regards, our results show a positive story for the case of Spain: on average, higher levels of productivity and the introduction of new production processes significantly enhance the likelihood of both starting a HG spell and making it longer.

Taking stock of all these results, we put forward that scholars interested in HGFs should complement firm-level analyses with episode (spell)-level investigations. HGEs may be the proper target for economic policies aimed at fostering dynamic economies (Bravo-Biosca et al., 2016).

The paper proceeds as follows. Section 2 reviews the relevant literature on HGFs. Section 3 introduces the dataset and the construction of the main variable employed in the empirical analysis. Section 4 illustrates the econometric analysis. Section 5 concludes the paper.

2. Related literature

2.1 Nature and determinants of high-growth firms: regularities and open issues

Schreyer (2000), in his seminal work, characterized the profile of the HGFs along several dimensions. The author defined[3] them as the firms with more than 20 employees that, during the period from mid-1980s to mid-1990s grew the most (top 10% of the growth rate distribution) across seven OECD countries. Schreyer also showed that smaller size and younger age are significantly associated to high-growth. Moreover, high-growth firms were not particularly relevant in any specific industry or territory. Finally, a positive association emerged between HG and several innovation metrics (i.e., R&D expenditures and R&D personnel shares). These results have been confirmed by subsequent studies, across industries, countries and over time. For example, Henreksson and Johansson (2009) and Anyadike-Danes et al. (2009) confirm that HGFs are generally active in all industries. Across countries, the youngest firms are consistently the fastest growing ones (see Haltiwanger et al., 2013; Lawless, 2014; Barba Navaretti et al., 2014; Manaresi, 2018). As for the relationship between firm size and the likelihood of being a HGF, Moreno and Coad (2015) put forward that there is mixed evidence. As for innovation, there is a consensus that while product innovation is beneficial for HG (when measured in terms of sales or employment), process innovation may have an adverse effect on employment, due to its labor-saving nature, but this may be counteracted by multiple "compensation effects" (Vivarelli, 2014).

Nonetheless, several issues regarding the determinants of HG may well deserve more attention. First, factors that explain the starting of a HGE may not symmetrically provide an explanation for the persistence in this growth state. In our empirical model (see Section 3.1), the probability of passing from NHG to HG and the probability of persisting in the HG state (that we model as *no transition* from HG to NHG and which leads to a longer HG spell) from *t*-1 to *t* are both explicitly considered and may be associated with different sets of determinants.[4] Second, while different phases of the business cycle may play a role (Henrekson and Johansson, 2010) in moderating or enhancing the effect of some of the determinants of HG over time, these have been rather neglected in the extant literature on high-growth. Third, while several studies have inquired into the role of market- (demand) related factors in firm growth (Foster et al., 2016; Pozzi and Schivardi, 2016), their role for HGFs is still largely unexplored, being the literature mostly centered in the supply-side factors.

In order to provide an answer to these issues, we employ a methodology that allows us identifying the transitions from NHG to HG and vice versa and analyze their (possible) different determinants. Among those factors, we inquire into the role of market-related factors. Moreover, we exploit about

[3] The definition of (what constitutes) a HGF is not trivial issue (Coad et al., 2014): indeed, the choice of the growth metric may well affect the results of the analyses (Delmar et al., 2003; Daunfeldt et al. 2013). The reader is cross-referred to Section 3, in which we introduce the definition of HG employed in this work.

[4] In a robustness check, we jointly estimate the equations modeling the two types of transitions, allowing for non-zero correlation across the unobserved variables that affect both HG and NHG durations within the firm.

25 years in the recent life of Spanish manufacturing to assess the role of the different phases of the business cycle for the transitions between states.

2.2 Persistence in high-growth: any evidence of it?

The empirical evidence so far provides –at best– very weak evidence of the ability of those firms that experience a HGE in one year to repeat their performance the year after. Several studies have shown a very low degree of persistence in the HG state. Parker et al. (2010, p. 209) have studied the behavior of a sample of about 100 "[…] non-subsidiary, medium-sized and UK-owned […]" high-growth firms observed between the beginning of the 1990s and the beginning of the 2000s. These authors put forward that "[…] gazelle-like growth appears to be fragile […]" with a fail by those firms to repeat their one-year tremendous performance in succeeding years. Daunfeldt et al. (2013), by employing a sample of Swedish companies in the period 1997-2010, have found that high-growth firms are not persistent in their performance. Daunfeldt and Halvarsson (2015), by employing a database covering all active Swedish firms in the period 1997–2008, have shown that fast-growing firms in a period were, on-average, shrinking firms in the previous period, while showing a low probability of being again HGFs in the following years. Coad (2007b) has studied the autocorrelation of annual growth rates in a dataset of French firms in the period 1996-2002: small firms that experience "extreme" growth performance (either positive or negative) in a given year, show a negative autocorrelation coefficient. Conversely, and at odds with previous studies in the field, López-García and Puente (2012) show, in a sample of Spanish limited liability companies observed in the period 1996-2003, that past high-growth positively affect the probability of current high-growth.

Other studies have taken a different perspective and tried to point out the characteristics that make persistent HGFs different from those which experience tremendous growth performance just occasionally. Bianchini et al. (2017) put forward that persistent HGFs are not different (in terms, for example, of productivity and financial structure) from occasionally HGFs in a sample of companies active in four European countries. Moschella et al. (2019) have found that some relevant characteristics of the firm (such as productivity and innovation, profitability and the financial structure) are not able to pick persistent HGFs out in a sample of about 23000 Chinese manufacturing firms observed in the period (of China's Miracle) 1998-2007. Guarascio and Tamagni (2019), by using the same firm-level data on Spanish firms that we employ in this work, adopt a growth-regression strategy to assess the role of past persistent innovation (seven out of ten years of consecutive innovation in the period 1990-1999) in succeeding sales growth over a 12-year period (2000-2012). Results point to persistent innovators not growing more or in a more persistent way than others firms. A common characteristic of these works, which -at the same time- constitutes a limitation, is that the usual time-span covers about a decade, which may be a short period of time if one wants to track the episodes of HG over time and take into account different phases of a business cycle.

Nonetheless, some scholars have had access to long-in-time dataset. Coad and Hölzl (2009) have employed an extensive database of Austrian firms in few services sectors over a 30-year period and studied the serial autocorrelation of 1-year growth rates in employment across different size classes: results confirm the negative autocorrelation of annual employment growth for fast-growing micro firms. Because of the data, they can only control for firm size and year effects in their regression, while no eventual asymmetries can be uncovered in the determinants of transitions from both low- or negative growth to a high-growth and vice versa. By using the same source of data, Hölzl (2014) has explored the performance of the firms in terms of survival and growth, both 3 and 9 years after a HGE: results, which are robust to a propensity score matched sample technique, confirm a low persistence in HG. The author imposes a certain structure to the dependency of future growth on past high-growth, (i) by estimating the effect after a specific number of years and (ii) by focusing on just one type of transition i.e. from a HGE to a similar one (persistence) or to a NHG episode, while the other way round transition is not explicitly explored. Dosi et al. (2019), by employing a sample of US listed manufacturing firms in a very long period (1959-2015), show that while there are cases of (even high) growth persistence across firms, these are rare but not fully accounted by a random process.

The closest paper to our work is the recent one by Bianchini and Pellegrino (2019), who adopt duration methods to assess the relationship between innovation persistence and persistence in employment growth in a sample of Spanish manufacturing firms covered by the *Encuesta Sobre Estrategias Empresariales* (ESEE), the same source of data we employ in this paper (see Section 3.1). However, with respect to their work, we add four major contributions. First, while Bianchini and Pellegrino (2019) focus on the persistence in positive employment growth and the role of innovation in it, we analyze two types of transitions between growth states (i.e., from NHG to a HG and vice versa). Indeed: (i) the transition from HG to NHG is relevant *per se*, as a proper way to study persistence in HG; (ii) the two transitions may be explained by different sets of determinants. Second, and very much connected with the first point, we assess the role of a broader set of potential determinants of the two types of transition, by including characteristics of the spell, the firm and the market in which the firm is active. Third, we inquire into the role of the business cycle in the determinants of transitions, by looking at the recent years of expansion and contraction of the Spanish economy to assess if these determinants have been different before and during the Great Recession.

Fourth, in the last part of the empirical analysis we focus on those HGEs that last longer, to inquire into their determinants.

3. Data and descriptive analysis

3.1 Growth states, spells and transitions across states

Our analysis uses firm-level data, extracted from the ESEE,[5] a (non-mandatory) survey sponsored by the Spanish Ministry of Industry and carried out by the Fundación SEPI. The sample is representative, at the industry-level, of the population of Spanish manufacturing firms with more than 10 employees.[6] The dataset presents at least three features that are key to the purpose of the present work. First, the time span covered by the ESEE is rather long. Indeed, the initial sample we consider is an unbalanced panel of about 2,000 manufacturing firms per year, in the period 1991-2015. This allows us to observe many firms experiencing both HG and NHG episodes. In addition, the period embraces different phases of the business cycle, i.e. the (pre-recession) expansionary phase and the years of the Great Recession, which hit the Spanish economy hard. Second, and very much connected with the first point, most firms show multiple spells of HG and NHG. We exploit this within-firm variability in the empirical model to disentangle unobserved heterogeneity from genuine duration dependence (Heckman, 1981). Third, the ESEE has a multi-scope nature, which allows us to consider a rich set of factors as determinants of both HG and NHG episodes.

In order to spot the episodes of HG and NHG, track their length and identify the transitions across the two states over time, we need first to choose a proxy for firm size, second, to calculate the yearly growth rate, and third, to define what the states of HG and NHG refer to. As for firm size, in this work we mostly use the information provided by the ESEE about firms' employment. Thus, $SIZE_{it}$ it is equal to the sum of full-time permanent workers of firm i, plus 50% of part-time permanent workers (both as of 31st December) and the average number of non-permanent workers throughout the year t, i.e., taking into account the quarterly number of non-permanent employees. As a robustness check we further replicate the empirical analysis, by employing another commonly used proxy for firm size, i.e. (real) sales.[7] Growth is defined as the 1-year log difference in firm size, as it follows:

[5] Comprehensive information about the ESEE survey can be found at https://www.fundacionsepi.es/investigacion/esee/en/spresentacion.asp.

[6] The sampling scheme is conducted for each manufacturing NACE class (2-digit) level. Companies employing between 10 and 200 employees are chosen by a random sampling scheme and the rate of participation is around 4%. For firms employing more than 200 employees, the rate of participation is about 60%.

[7] In the words of Sutton (1997; p. 40) "'Size can be measured in a number of ways […) annual sales, […] current employment, and […] total assets. Though we might in principle expect systematic differences between the several measures, such differences have not been a focus of interest in the literature".

$$gr_{it} = \ln(SIZE_{it}) - \ln(SIZE_{it-1}).$$

In line with the previous literature, we focus on episodes of organic growth. Indeed, the vast majority of actual growth episodes are due to an internal expansion of the firm in terms of its capacity and output. Moreover, the decision about undertaking mergers and acquisitions (M&As) is intrinsically different from a growth strategy based on the own resources (Rumelt, 1987; Lockett et al., 2011).[8]

We employ a *relative* definition of high-growth. A firm is defined in the HG state in year t (HG_{it}=1) if gr_{it} is in the top decile of the sample distribution of employment growth rates.[9] We take the three-year moving average (from $t-1$ to $t+1$) to build the employment growth rate distribution, as the reference to which compare each yearly firm growth rate. This choice is motivated by the aim of smoothing the growth rate distribution to reduce the distortionary impact of recessive years with extraordinary employment reduction.[10] Figure 1 shows the value of the 90th percentile of the growth rate distribution in each year and the reference value with the three-year window. We build the two growth states as mutually exclusive and complementary, thus a firm which is not classified in the HG state in year t, it is necessarily classified in the NHG state in the same year (NHG_{it}=1).[11]

[Insert Figure 1 about here]

The duration of a HG (NHG) spell is equal to the number of consecutive years in which a firm remains in that state, since its beginning. A HG (NHG) spells ends in year t if the firm is in that state in year t and not in year $t+1$. Hence, the information in 2015 is only used to determine whether ongoing spells in year 2015 end in that year or are right-censored (that is, they continue beyond 2015). The HG (NHG) spells that end without a transition to the other state are included in the analysis and treated as right-censored. This category includes (apart from episodes at the end of the observation window) the exits from the sample either due to failures or M&As, no further collaboration with the

[8] Admittedly, firms in the sample grow either organically or via M&As. For the purpose of this work and in order not to lose the information provided by firms which go through M&As or spin-off procedures, we identify episodes of non-organic growth at the moment in time in which they happen (year t). We consider the pre-episode (up to year $t-1$) and post-episode (from year $t+1$ onwards) units of analysis as two separate spells.

[9] Admittedly, while our definition resembles Birch's (1981) definition, an absolute definition may also be used, as the one proposed by the Eurostat-OECD Manual on Business Demography Statistics (2007). The manual defines a HGF as one which (i) initially possesses 10 or more employees or that has at least four times national per capita income in annual revenues, and (ii) experiences average annualized employment or revenue growth of greater than 20 percent over a three-year period. While the debate about what constitutes a HGF is non-trivial (Coad et al. 2014), it is beyond the scope of this work. Only for comparison purposes with the definition advocated by the OECD Eurostat Manual, we report that about 3% of firms fulfill the criteria of having a cumulative average growth rate larger than 20% for three consecutive years.

[10] For example, in 2009 (the worst year for employment in Spain), for example, the 90th percentile was 0.0453, which contrasts sharply with 0.198 in 1995.

[11] The NHG state comprehends a heterogeneous set of growth episodes (from mildly positive to very negative), thus gathering a lot of heterogeneity. Some of these episodes may be interesting *per se* (such as the high-decline firms, as suggested by Coad et al., 2014) but the exploitation of the heterogeneity within the NHG state is beyond the scope of this work.

survey or due to other re-structuring processes.[12] Both the descriptive and the econometric analysis are restricted to "fresh" spells. Left-censored spells (i.e. spells started before 1991) are indeed excluded from the sample, due to the well-known bias they generate in the estimation procedure. The whole procedure detailed above reduces the usable time span to the period 1994-2014, which covers 2832 HG spells and 4934 NHG spells corresponding to 3562 firms.

For illustrative purposes, Figure 2 (*Panel A*) provides an example of HG and NHG episodes that occur within a hypothetical firm *i*. If 1999 (2005) is the first (last) year in which the information on employment is available for this firm, 2000 (2005) is the first (last) year in which the growth rate can be computed. Firm *i* has two spells of NHG and one spell of HG. The first spell of NHG starts in 2000 and ends in 2002, while in 2003 a HG spell starts which last for just one year. In 2004 a second spell of NHG starts, which ends in 2005. From 2006 onwards, the second NHG spell is right-censored.

[Insert Figure 2 about here]

An analysis of the spells (yearly series) of HG and NHG is reported in Table 1, where the numbers and shares of NHG and HG spells are shown, in cols. 1 and 2, in terms of their length; additionally, the NHG and HG spells of maximum length within each firm are shown in cols. 3 and 4. While almost all firms in the sample (3446/3562=96%) show a positive number of spells of NHG, much less of them – although not few—show spells of HG (1897/3562=53%).

Moreover, the restricted average length of a NHG spell is about 4.37 (=21585/4934) years, while this drops to 1.18 (=3362/2832) years for the spells of HG.[13] While it is not so rare to experience an episode (spell) of HG over more than two decades, this is typically short.

[Insert Table 1 about here]

Another way of looking at the same phenomenon is to estimate the hazard rate of a certain spell, which is equivalent to the probability of transition to the other growth state, after having been in the departure state for 1 year. While for the NHG spells the first year hazard rate is equal to 0.10, for the HG spells is much higher (0.76). Once a firm starts an episode (spell) of HG, this will end the subsequent year in almost 8 out of 10 cases. Furthermore, while the maximum length for a HG spell is equal 6 years, it is equal to 21 years (i.e., the maximum length of the observed period) for a NHG spell. Another interesting evidence is that for both NHG and HG, the total number of firms is higher than the total

[12] There exists hardly no difference in the rate of exit from the sample between the HG and NHG states.
[13] It corresponds to the simple mean of observed durations both for complete and right-censored spells.

number of spells, especially for short-length spells, thus suggesting that most firms experience more than one spell.

3.2 Determinants of transitions across growth states

The factors that affect the two types of transitions have been grouped into six categories for ease of interpretation: (i) variables capturing the characteristics of the spell, (ii) the structural characteristics of the firm, (iii) productivity and innovation, (iv) proxies for alternative growth strategies, (v) the firm financial structure and (vi) the market (demand) which a firm faces. Additionally, year and industry effects (at 2-digit level, NACE-rev.2) are also included. Table 2 describes how all variables have been built and shows some descriptive statistics.

[Insert Table 2 about here]

Two set of variables account for the characteristics of the (HG or NHG) spells. First, three binary variables control for the age of the spells (*SP_LENGTHg*), where $g = \{1,2,3\}$ if, respectively, the age of the current spell is equal to 1 year, 2 years or 3 years or more.[14] Second, another set of three binary variables (*SP_REPg*), where $g = \{1,2,3\}$ gather the spells in terms of those being respectively the first, the second, or the third or higher order repeated spell of the same type for the firm. Figure 2 (*Panel B*) provides an exemplification of how these two variables take their values for a hypothetical firm i. In the empirical model, the coefficient associated with the variable *SP_LENGTHg* captures the relationship between the likelihood of ending the spell (i.e., the transition to the other growth state), and the length of the current spell. The coefficient of *SP_REPg* captures the relationship between the likelihood of ending the spell and the fact that the firm has already experienced a spell of the same type in the past. These two variables are key to point out the "episodic" and/or dependent-on-past-firm-experience nature of the HG phenomenon.

As for firm characteristics, the literature has consistently emphasized the effects of firm size and age as crucial variables in explaining firm growth (see Hall, 1987; Lotti et al., 2009; Haltiwanger et al., 2013; Barba Navaretti et al., 2014; among others). For these reasons, firms have been classified, respectively, into five size and five age groups (*SIZEg, AGEg,* where $g = \{1,2,3,4,5\}$) at onset of each spell they experience, thus a within-firm variability of these variables is ensured from one spell to the other. Productivity has been put forward as one of the key drivers of firm performance (Esteve et al.,

[14] In order to avoid an odd behavior in the estimated baseline hazard functions due to scarcity of observations spanning longer durations, we right-censor spells of HG longer than 3 years. Likewise, to make the results comparable for the two transitions, we apply the same right-censoring to NHG spells, which is also supported by piecewise estimates of the baseline (not reported, but available from the authors upon request) that suggest no significant differences in hazards for across different spell ages.

2018), both by dynamic competitive equilibrium models (Jovanovic, 1982; Ericson and Pakes, 1995) and evolutionary theory (Nelson and Winter, 1982; Dosi et al. 1995). In our empirical setting, *PRODUCTIVITYg*, where $g = \{L, M, H\}$, is proxied by the ratio of sales to employee, and firms are grouped into "low-", "medium-" and "high-productive" firms by comparing, in year *t*, each firm's productivity with the 25th and 75th percentiles of the sample productivity distribution. Innovation shapes fast size dynamics (Coad and Rao, 2008), and it is proxied by two binary variables that measure whether the firm had introduced any product (*PROD_INN*) or process innovation (*PROC_INN*) in year *t*.

Firms may grow as consequence of an international expansion of their activities (Grazzi and Moschella, 2018), while being part of an industrial group or corporation may affect their growth pattern. Accordingly, two binary variables (*EXPORTER* and *GROUP*) are included, taking value 1 in year *t* if the firm, respectively, exports or belongs to an industrial group, and 0 otherwise. It is also well known that the lack of availability of external financial resources may constraint firm growth (Carpenter and Petersen, 2002; Hutchinson and Xavier, 2006; Clarke et al., 2012). We employ a widely used figure to capture the financial structure of the firm in terms of its balance of external and resources, i.e. the leverage ratio (*LEVERAGEg,* where $g = \{L, M, H\}$), calculated as the ratio of debts over debts plus shareholders' equity. Similar to productivity, we include a vector of dummies which gather "low-", "medium-" and "high-leverage" firms by comparing each firm's leverage ratio with the 25th and 75th percentiles of the sample leverage distribution.

Two variables have been included to account for some relevant conditions of the principal market in which the firm is active and for the role of demand. First, a vector of three dummies is included, *MARKETDYNg*, where $g = \{R, S, E\}$, which have been built starting from a categorical variable capturing if the market is, respectively, going through a "recessive", "stable" or "expansive" phase. Second, based on a categorical variable that measures the firm's market share evolution, three dummies have been included, *MARKETSHg*, where $g = \{D, S, E\}$, which groups those firms whose market share is respectively, "decreasing", "stable", "expanding". It is relevant to underline that both for *MARKETDYNg* and *MARKETSHg*, the firm self-defines the boundaries of its main market, which does not overlap with the 2-digit level industry definition, while being at a much finer level of disaggregation. This is key to better capture some main characteristics of the demand faced by the firm.

As for firm and market characteristics, while *SIZEg* and *AGEg* are measured at the onset of the current spell, all other variables have been introduced in the empirical model as 1-year lagged to mitigate simultaneity issues.

4. Econometric analysis

4.1 The empirical model

This paper analyzes the dependence of the exit from non-high growth (NHG) and from high growth (HG) on the length of time in an NHG or HG spell and on other explanatory variables by the estimation of duration models. At any point in time, a firm *i* may be in any of two states indexed by s (s = HG, NHG), and S_{tji} denotes the state occupied by firm *i* during interval *t* of episode *j* (i.e. firms may show more than one HG and/or NHG spells). We estimated the probability that a firm leaves NHG or HG during period *t*, given that it has been in NHG or HG for *t-1* periods. Since we have yearly information, we treat duration as a discrete variable and estimate discrete time duration models. Let us define y_{tji} as a binary variable indicating whether any transition (i.e., an exit from the spell of NHG or HG) has occurred during interval *t*. The discrete-time hazard function for state *s*, defined as the probability of a transition from state *s* during interval *t*, given that no transition has occurred before the start of t, is:

$$\lambda_{stji} = Pr\left(y_{tji} = 1 \middle| y_{t-1,ji} = 0, S_{tji} = s\right), \qquad s = HG, NHG$$

We estimate the following multilevel two-state logit model:

$$log\left(\frac{\lambda_{stji}}{1-\lambda_{stji}}\right) = \alpha_s D_{stji} + \beta_s X_{stji} + u_{si}$$

Where D_{stji} is a vector of dummy variables that capture the age effects of a particular spell in state *s* by firm *i*. In particular, in the reported tables we have estimated models in which D_{stji} includes three dummy variables to control for age-of-spell effects (*SP_LENGTHg)*. X_{stji} is a vector of explanatory variables that affects the transition from state *s*, which includes characteristics of the spell (*SP_REPg)* as well as firm and market characteristics. Finally, u_{si} allows for unobserved heterogeneity between firms in their probability of shift *from* state *s*. There may exist unobserved firm-specific factors (constant across both episodes and states) that affect the hazard of an event for all episodes and states (e.g., managerial capabilities of the firms not captured by the included explanatory variables). We assume that $u_{si} = (u_{HGi}, u_{NHGi})$ follow a bivariate normal distribution, which allows for correlation between time-invariant factors that influences each transition.

In Sections 4.2 and 4.3 (main results), we assume that $cov(u_{HGi}, u_{NHGi}) = 0$, that is, we treat the two transitions as independent and model them with two separate equations (one for the transitions from NHG to HG and another one for transitions from HG to NHG/persistence in HG). Conversely, in Section 4.4. (robustness checks) we allow for $cov\left(u_{HGj}, u_{NHGj}\right) \neq 0$, and we estimate the equations for the two transitions jointly. By doing so, we take into account that, for example, a firm likely to start a HG episode if in a NHG state may also show a lower chance of ending a HG episode once in it.

4.2 Main results

We start with the estimation of the hazard of the NHG and HG spells separately.[15] The two hazard rates are functions of the duration of the current state, the order (repetition) of the current spell, year and industry effects and firm unobserved heterogeneity. The results of the random effects logit models for the two types of transitions are shown in Table 3, where in col.1 the hazard rate for NHG spells is the dependent variable, while in col. 2 the hazard rate refers to HG spells. All the coefficients in the tables showing the econometric results have been exponentiated and are interpreted as odd ratios with respect to the baseline (omitted) category.

[Insert Table 3 about here]

As for the characteristics of the spells, the effect of the length of the current spell on its hazard rate, as captured by the coefficients of the *SP_LENGTHg* variable (where *g* is equal to the length of the spell in either the NHG state in col. 1, or the HG state in col. 2) shows an asymmetric effect. While it does not play any role in explaining the likelihood of transition from NHG to HG (col. 1), it shows a negative effect on the hazard from HG to NHG, or, putting it differently, a higher persistence (of the firm) in the HG state. This effect is mildly significant for the second year of length of the HG spell (col. 2), but it is higher in magnitude and significance for the group of HG spells which last for 3 years or more. HG spells that reach their third year face a 61% lower risk ((1-0.389)*100) of ending the ongoing spell than a comparable --in terms of industry, year and order/repetition-- HG spell in their first year of existence. These two results are relevant. First, the preliminary evidence suggested that HG state is not "a destiny taken for granted" that all firms in the NHG state experience sooner or later. Second, the results in Table 3 suggest the existence of true state dependence. That is, after a strong initial selection effect, HG that survive beyond their first year significantly increase their survival chances in HG state. We find no evidence of a similar effect for NHG episodes.

The effect of the repetition/s of the current spell on its hazard rate is captured by the coefficients of *SP_REPg* (where *g* is equal to the order of the spell in either NHG in col. 1 or HG in col. 2). In col. 1, these coefficients show that for the average firm with more than one NHG spell, the third or higher order NHG spell shows a significant (about (1-0.60)*100 = 40%) lower probability of ending with respect to the first NHG spell.[16] This result, which is coherent with the evidence provided by previous works on the negative autocorrelation of growth rates (Coad, 2007b), suggests that for the average firm which has already experienced two transitions from NHG to HG, it is more difficult to experience

[15] This is equivalent to say that we estimate the conditional probability of shifting from a growth state to the other, being the two growth states complementary and mutually exclusive.

[16] In the model for the transitions NHG to HG, we cannot reject the existence of unobserved (cols (1) in Tables 3 and 4). Hence, the regression coefficients for this model are defined conditional on the unobserved heterogeneity. Hence, the impact of each covariate holds valid for two spells with identical frailty term.

a third one in a sort of "erratic" pattern (Coad, 2007a; Guarascio and Tamagni, 2019). Additionally, results in col.2 show that repetition of HG episodes does not increase survival chances.

These results on the characteristics of the spells are, in our view, coherent with the fact that it is hard to identify series of episodes (spells) of HG within the firm even over a long period of time, while there are (few) episodes that show a relative long duration and a self-reinforcing effect as their length increases.

As for the year dummies, no significant differences exist across years in terms of higher/lower probability of ending a NHG spell/starting a HG spell, except for 2008 and 2011 in which the probability for ending a NHG spell is significantly lower (about 64% lower (1-0.36) in 2008 and about 55% lower in 2011) than in the baseline, year 1994. Interestingly enough, year dummies are even less effective in explaining persistence in the HG state, as shown in col. 2: indeed, few of them (1998, 2002) are only mildly (at 10%) significant. As for the industry dummies, results generally confirm the previous evidence (see Schreyer, 2000; Bianchini et al., 2017; World Bank, 2019; among others) on a rather minor role played by industrial specificities in explaining HG episodes (col.1) and, mostly, persistence in HG (col.2).[17]

Next, we move to a more refined specification, which contains a larger vector of regressors.[18] The results are shown in Table 4 and factors that affect the two types of transitions are grouped into six categories, as explained in Section 3.2.

[Insert Table 4 about here]

The length and the order of the current spell maintain the same relationships with the likelihood of spell ending (i.e. transition to the other growth state) that we found in the more parsimonious specification of Table 3. The longer length of the current spell continues to be significant in explaining a higher persistence in the HG state, but only for those spells which last for 3 or more years (captured by the coefficient of SP_LENGTH_3, in col. 2) with respect to spells which are 1-year old. Conversely, having experienced past episodes (spells) of HG in the past does not ensure higher persistence in HG with respect to firms that are in their first HGE (non-significant hazard ratios of SP_REP_2 and SP_REP_3 in col. 2). Additionally, if a firm has already experienced two past episodes (spells) of NHG, the current NHG spell shows a lower probability of ending (captured by the coefficient of SP_REP_3

[17] Indeed, while no industry shows a statistical significant difference in explaining persistence in HG, "Leather, fur and footwear" and "Timber" show, for firms belonging to them, higher probabilities to experience a HGE than the reference industry ("Meat related products"). Conversely, "Printing and publishing", "Chemicals" and "Basic metal products" all show lower probabilities for their firms to experience a HGE with respect to the reference industry.

[18] In all the following specifications, we include both year and industry dummies but we avoid reporting their (consistent) coefficients to save space. Complete tables are available from authors upon request.

in col. 1), *ceteris paribus*. Again, these results suggest both the "episodic" nature of high-growth and the "erratic" patterns followed by those firms that experience multiple episodes of HG.

As for firm age and firm size, results in Table 4 largely confirm the previous literature on HGFs. In particular, by looking at col. (1), which refers to transitions from NHG to HG, older firms show significant lower probability of experiencing a HGE with respect to their younger counterparts, and the firms with the largest "disadvantage" are precisely the oldest ones. Indeed, firms established since more than 30 years, as captured by the hazard ratio of AGE_5, show a likelihood of passing from NHG to HG which is about 53% (1-0.469) lower than *start-up* firms (AGE_1, the baseline, omitted category, defined as firms established since at maximum five years). By looking at col. (2), we can also appreciate that age plays a negative role in the permanence in the HG state (or, in other words, a positive role in the transitions from HG to NHG). For example, we may quantify as about 94% lower the likelihood of persistence in the HG state for firms established since more than 30 years (AGE_5) with respect to *start-up* firms (AGE_1). The role of firm size largely mimics that played by firm age, with firms with a larger size than the baseline (omitted category: $SIZE_1$, from 10 to 20 employees) consistently showing lower probability of experiencing a HGE. However, as for the persistence in HG, larger size is not necessarily a disadvantage: indeed, firms that employ more than 500 employees do not show a lower probability of persistence in the HG state (shown by the not significant coefficient of $SIZE_5$) with respect to the smallest ones. This result is in line with the previous literature: for example, Schreyer (2000) showed that large firms gain in relevance when one considers high-growth episodes, instead of considering positive but moderate growth episodes (where large firms are less frequent).

The probability to shift to the HG state is more than 80% higher (col. 1) for the most productive firms ($PRODUCTIVITY_H$) with respect to the baseline group (the least productive firms, $PRODUCTIVITY_L$). The effect rises as one moves from the category of the least productive to the category of the most productive. At the same time, and especially for the most productive firms, these also show a higher persistence in the HG state (by about 42%, as shown by the hazard ratio associated with $PRODUCTIVITY_H$ in col. 2). This is interesting because it suggests that, on average and in the period from 1994 to 2014, the most productive Spanish manufacturing firms have been the ones that more frequently have experienced episodes of fast employment growth. Even though Arnold et al. (2011) have provided some negative evidence the relationship between firm growth and productivity for the case of Spain in the period 1998-2004, our results provide a positive message about the allocation of the labor input, at least for the fastest-growing firms. The introduction of a process innovation raises the probability of shifting from NHG to HG, as shown by the hazard ratio of *PROC_INN* in col. (1), which corresponds to a 25% higher probability of experiencing a HGE, for those firms having introduced a new (and likely more efficient) production process, with respect to their counterparts. This result is consistent with Harrison et al. (2014), who show the growth in demand for old products due process innovations that lead to higher efficiency and may well compensate the labor-saving effect of this type of innovation. However, process innovation has not a significant on HG persistence (col.2). Unexpectedly, we neither find a significant association (non-significant hazard ratio of *PROD_INN*) between product innovation and the likelihood of experiencing a HGE (col. 1), nor with persistence in the HG state (col.2). This result might be explained by the long payback times that characterize the returns associated to the introduction of a new product in the market (Grabowski et al., 2002). Moreover, the relationship between product innovation and firm growth is complex and it may change according to firm characteristics, the nature of market selection and the geographical environment (Audretsch et al. 2014).

As for the alternative ways through which a firm may grow, belonging to an industrial group of firms both reduces the probability to start a HG spell (by about 20% with respect to independent firms, in col. 1) and increases the probability of persistence in the HG state (by about 25% with respect to independent firms, in col. 2). Thus, belonging to a group may "smooth" firm size dynamics in terms of labor input via a re-allocation of resources within the group. We find that being an exporter significantly reduces the likelihood of experiencing a HGE (by about 15% with respect to a non-exporter) and does not ensure a higher persistence in the high-growth state. However, this may be due to the fact we measure firm size with the number of employees and that exporting abroad does not necessarily entail a significant increase in the staff at home.[19] The firm's financial structure does not play a significant role in explaining the higher/lower likelihood of experiencing a transition from NHG to HG, nor of persistence in the HG state.

We next move to analyze the characteristics of the market (demand) that a firm faces. A "stable" or "expansionary" phase of the market ($MARKETDYN_S$ and $MARKETDYN_E$) ensure a higher likelihood of shifting to HG with respect to the firms active in a "recessive" market (respectively about 38% higher for firms in a market in a stable phase and 74% higher for firms in a market in an expansionary phase, as shown in col. 1). At the same time, the expansionary phase of the market significantly raises survival chances in HG state: *ceteris paribus*, firms active in a market experiencing an expansionary phase are characterized by about 35% higher probability of continuing in the HG state in year $t+1$, conditional on being in that state in t. The information about the evolution of the firm's market share –that once controlled for productivity may be a proxy for the firm's specific market power-- provides other additional insights. Indeed, an "expanding" market share is associated

[19] Indeed, in Section 4.4.1, we replicate the analysis by measuring firm size with (real) sales and we do find a significant positive association between being and exporter and the probability of shifting from NHG to HG.

with a higher probability for the firm to start an HG episode, *ceteris paribus*, with respect to the case in which the market share is "decreasing". As these results show, both the evolution of the market (demand) and the firm market power, which have been seldom considered by previous studies, are important and complement supply-side factors in explaining the probability of transition to the HG state, and –even to a lesser extent—also the permanence in it, as time passes.

Overall, these results point out three facts. First, the coefficient of the variables capturing the characteristics of the spells (*SP_LENGTHg* and *SP_REPg*) show that HG has an "episodic" an "erratic" nature. On the one hand, while few spells survive more than three years, those making it beyond that substantially rise their survival chances. On the other hand, having experienced past episodes of HG does not ensure a higher probability of repeating it. Second, after accounting for these spell characteristics, firm and market characteristics still matter. Indeed, NHG spells in younger, smaller and more productive firms show a higher hazard rates than their counterparts, which correspond to a higher probability for these firms to experience a HGE, starting from the NHG state. At the same time, the expansionary dynamic of the market and of the firm's market share also are both associated with a higher probability of transiting from NHG to HG. Third, once we focus on the HG spells and their hazard rate, most of the characteristics that explain a higher probability of starting a HG spell (younger age, smaller, size, higher productivity, being active in a market in its "expansionary" phase) are also associated with a higher likelihood of persisting in the HG state. However, given that it is rare for a firm to experience HGEs that are longer than 1 year (only about 5% of firms show HGEs that last for 3 years or longer), it is harder to "characterize" persistence in HG than the transition from NHG to HG, even with our large set of determinants (Dosi et al. 2019). In Section 4.3, we will deepen the analysis of the determinants of the length of a HG spell and of the repetition of it within a firm, as time passes.

4.3 Further results

4.3.1 The Great Recession

One of the advantages of employing a dataset that covers the Spanish manufacturing over about two decades is that we can not only embrace different phases of the business cycle in our analysis, but we may also interact them with the vector of determinants of the two types of transitions. Indeed, some factors which explain the transition from NHG to HG, or the persistence in the HG state from on a year-on-year basis, may well depend on the phase of the business cycle the national economy is passing through. To this end, we include in the empirical model a dummy variable, *D_DOWNTURN*, which is equal to 1 for the period 2008-2014, while being equal to 0 for the period 1994-2007. For ease of reading, Table 5 shows only the variables whose interaction with the dummy capturing the downturn are significant and the respective calculations for the difference in the effect of the variable (on the likelihood of transitions) in the two sub-periods.

[Insert Table 5 about here]

Overall, few variables show an effect (on the likelihood of transition) that varies over the two main phases of the business cycle, but these are worthy to point out. First, during downturn and low growth from 2008 onwards the youngest and smallest firms are not the ones with the higher likelihood of experiencing an HGE, as they do during the upturn of the business cycle, while no changes are observable in relation to these two variables for the persistence in HG. This result is much in line with the evidence provided by Fort et al. (2013) and Criscuolo et al. (2014) on the sensitiveness of growth performance by young and small firms during the Great Recession. Second, the introduction of a new process shows a significant association with a higher probability of persistence in HG during the upturn of the business cycle (before 2008), but this effect reverses from 2008 onwards and it might be the sign of more labor-saving innovations in terms of processes adopted by the firms after the beginning of the Great Recession. Third, the higher persistence in HG associated with belonging to an industrial group during the expansionary phase is reduced from 2008 onwards.

4.3.2 Further exploration of HG spells

We complement our previous results with a specific analysis about what factors are associated with a longer/shorter length of the HG spells and with the (rare) repetitions of them within-firm and over time. Table 6 (col. 1) shows the breakdown of the HG spells in terms of three categories, based on their length (i.e., one, two, or three years or more). Overall, 2,517 HG spells have occurred across 1,582 firms during the period 1993-2014. Right-censored spells are dropped in order to avoid biases due to incomplete information.[20]

[Insert Table 6 about here]

Table 6 (col. 2) shows, instead, the breakdown of firms in terms of the number of HG spell repetitions. In particulars, three groups are defined, where the third category refers firms that have three or more repetitions of HG spells. As expected, the most frequent situation corresponds to firms that experience only one HG event, though 35.5% of firms have more than one HG spell.

[20] As previously explained, the duration analysis includes and treats properly right-censored spells. However, in this complementary analysis, a one-year HG spell that is right censored could be inadequately assigned to state 1, while it is true and unknown length could be larger.

In accordance with the ordinal nature of the three categories, an ordered logit specification is applied. In this context, Y^* is the latent variable that crosses progressively higher thresholds, where $Y_i^* = \beta X_i + \varepsilon_i$. For example, in the case of HG spell length, three categories are defined by two thresholds (α_1 , α_2) such that if $Y_i^* \leq \alpha_1$, then the length is one year, if $\alpha_1 < Y_i^* < \alpha_2$ then the length is two years and, finally, if $Y_i^* \geq \alpha_2$, then the period is longer than two years. The *j*-category probability (*j=1,2,3*) is defined as $\Pr(Y_i = j) = F(\alpha_{j-1} < Y_i^* \leq \alpha_j) = F(\alpha_j - \beta X_i) - F(\alpha_{j-1} - \beta X_i)$, where F is the logistically distributed function. Two thresholds parameters are estimated in our setting (intercept is excluded); if they are significantly different each other, it suggests that they should not collapsed into less categories (two, in this case). As is well known, ordered logistic regression assumes that the coefficients that describe the relationship between category 1 versus categories 2&3 of the response variable is the same than between categories 1&2 versus category 3. This is called the proportional odds assumption or the parallel regression assumption. If the assumption is met, then all the coefficients (expect the constant) should be equal across different logistic regressions, other than differences caused by sampling variability (Williams, 2016). If that assumption is not fulfilled, a generalized ordered logistic regression is required in order to relax that assumption. However, some explanatory variables can meet the proportional odds assumption, while others do not. The partial proportional odd model is an intermediate model between both extremes, the ordered logit and the generalized ordered logit, in which some variables are constrained to be the same across values of j-categories, while others are not. A set of tests is carried out in an iterative process to identify, for each coefficient, whether a less constrained approach is required.[21]

As it is common in discrete choice models, estimated parameters indicates the sign, but not the magnitude of impacts. Therefore, Table 7 shows *average marginal effects* for some selected significant variable. Marginal effects are evaluated for each state of the dependent variable, *ceteris paribus*. As it can be appreciated, the largest and oldest firms have larger probabilities of having a HG spell of 1-year length and, correspondingly, smaller probabilities of longer HG spells. Additionally, being active in an expansive market or carrying out process innovation all increase the likelihood of experiencing longer HG spells. For example, while very large firms are 6.5 percentage points less likely than smaller firms to experience a two years spell duration, being in expansive

[21] Col. 1 of Table A.1, in the On-line Appendix, shows the β estimated parameters for a partial proportional odds model with spell length as dependent variable. Only the dummy variable that measures “high” productive firms (*PRODUCTIVITY$_H$)* fails to meet the proportional odds assumption. Accordingly, the results for both unconstrained coefficients are showed in that case.

markets or carrying out process innovations are more likely to experience a spell with such a duration, *ceteris paribus*.

[Insert Table 7 about here]

Figure 3 shows the *average adjusted predictions* for the three categories of the ordinal dependent variable and each state of the explanatory binary variables. As we already know from Table 6, the first category (HG spells that last for one year) gather a large mass of probability, while the third category (HG spells that last for three years or more) is relatively small. The corresponding changes (i.e., marginal effects) are not large in absolute terms, but they are in relative terms. For example, carrying out process innovations increases 1.0 percentage points the predicted probability of having a three or more years HG spell (from 3.0% to 4.1%), which represents a relevant increase in likelihood (37%) with respect to firms than do not carry out process innovations.

[Insert Figure 3 about here]

Finally, the last column in Table A.1 in the On-line Appendix shows the results of the ordered logit estimation for repetition. However, a clear message that emerges from these results is the difficulty of explaining the pattern of HG repetition within firms: hardly any variable is significant in explaining the number of repetitions of HG spells.

4.4 Robustness checks

4.4.1 Sales as an alternative proxy for firm size

It is relevant to assess the robustness of our results to alternative proxies for firm size. We thus run again the analysis after having calculated the 1-year growth rate as the log-difference in (real) sales and having spotted episodes of HG and NHG.[22] Results are shown in Table 8.

[Insert Table 8 about here]

Apart from few changes in hazard ratios associated to some variables that explain the transitions from NHG to HG (productivity, being an exporter and belonging to an industrial group), the results regarding most of the firm and market (demand) characteristics for the hazard of both NHG and HG

[22] Sales have been deflated by using price variations defined at the firm level. Specifically, the surveyed firms give annual information about markets served (up to five), identifying their relative importance (in percentage) in total sales of the firm. This information allows us to calculate a price index for all markets and for each market, using the proportions with respect to total sales as weighting. Average (industry/year) price variations are used for those few firms that do not provide information.

spells in terms of (real) sales are confirmed. Consistently with our main results, the longer length of the current spell is significant in explaining a higher persistence in the HG state, especially for those spells that last for 3 year or more (captured by the coefficient of SP_LENGTH_3, in col. 2). Conversely, having experienced past episodes (spells) of NHG or HG does not ensure, respectively, a higher probability to shift to the HG state, nor a higher persistence in it, with respect to firms that are in their first HGE (non-significant hazard ratios of SP_REP_2 and SP_REP_3 in both cols. 1 and 2).

4.4.2 Joint estimation of HG and NHG transitions: a two-level two-state logit model

As anticipated in Section 4.1, the equations modeling the two types of transitions, i.e. from NHG to HG and from HG to NHG, may be characterized by a not independent error structure: for example, a firm may simultaneously have a higher likelihood of HG ins but a low risk of HG outs. In Table 9, we allow for this possibility, by estimating a two-level two-state random-intercept and random-coefficient logit model, allowing for correlated (firm-level) random effects across the two equations. We assume that the random effects follow a bivariate normal distribution to allow for correlation between the unmeasured time-invariant influences on each type of transition.

[Insert Table 9 about here]

The correlation coefficient between the vectors of random effects is positive and significant, thus pointing out that the likelihoods of the two types of transition are not independent. Firms with a higher likelihood of HG ins are also more likely of HG outs. Nonetheless, the main results shown in Table 4 are strongly confirmed. While the variable capturing the role of the length of the current spell for the likelihood of persistence in the HG state (col.2) maintain a comparable coefficient, the (negative) effect of "experience" is even reinforced. Indeed, when the equations for the two transitions are jointly estimated, the hazard ratio associated with SP_REP_3 puts forward that while the third spell of NHG in col.1 (HG in col.2) has a lower (higher) likelihood to end than to the first spell of NHG (HG). The younger and the smaller firms showing both a higher probability to experience a HGE with respect to their older and larger (but not the largest) counterparts and to persist more in that state. The most productive firms both show a higher probability to experience a HGE with respect to their less productive counterparts and to persist more in that state. Process innovation does boost the probability for a firm to experience a HGE, while it does not help the firm to repeat that performance. As for the market characteristics, being active in a market which is going through an "expansionary" phase is relevant for both a higher likelihood of experiencing a HGE and a higher persistence in the HG state, while being active in a stable market does not ensure the firm to repeat the HG episode. At the same time, a positive evolution of the market share is associated with a higher probability of experiencing a HGE, while it does not explain the persistence in it as time passes.

5. Concluding remarks

While in recent years high-growth firms have attracted the attention of scholars, policy makers and the popular press, several features of this group of firms are still not clear-cut (Audretsch, 2012; Coad et al., 2014). Among the open issues, we may outline the following ones. First, the controversial nature of the high-growth phenomenon, being this either fully "episodic" or –at least for some firms— rather "persistent". Second, the role of market (demand) characteristics on top of that played by firm (supply) characteristics in explaining the probability of experiencing a high-growth episode and the persistence in it. Third, the role of the different phases of the business cycle in explaining high-growth and its determinants. In this respect, this paper does three main things.

First, we have spotted the episodes (spells) of high-growth and non-high-growth in a representative sample of Spanish manufacturing firms with more than 10 employees over about two decades, by means of duration models. Episodes of high-growth are not uncommon, but they are usually short and very hard to repeat. Nonetheless, there are few episodes of high-growth that last for multiple years and show a self-reinforcing effect in the probability of lasting longer, the higher their length (duration dependence). These few episodes of high-growth which last for multiple years are mainly explained (other than age and size) by market dynamism and process innovations strategies. At the same time it is difficult to explain, and thus to predict, repetition of HG spells over time within the same firm. Second, in the empirical analysis we have included, together with spell characteristics, a vector of firm and market (demand) characteristics. Firm characteristics confirm the previous literature findings. Moreover, both the expansionary dynamic of the market in which a firm is active and of its proper market share positively affect the probability of the firm to experience a HG episode and to make it lasting longer. Third, we have explored the role of the business cycle in enhancing or hindering the role of the determinants in both experiencing a HG episode and in persisting in it. Few variables show a differentiated effect across the phases of the business cycle, but they bring interesting insights. In particular, while during the years of the Great Recession, the role of younger age and smaller size for explaining the transition from NHG to HG is reduced, no changes are observable in relation to these two variables for the persistence in HG. At the same time, the positive effect of introducing a process innovation for the probability of shift from the NHG state to the HG state in the expansionary phase is reversed during the Great Recession.

Taking stock of these results, we put forward that the researchers interested in HGFs should complement firm-level analyses with episode (spell)-level investigations. Episodes of HG may be the proper target for economic policies aimed at fostering dynamic economies (Bravo-Biosca et al., 2016). Policy makers may devote effort in designing policies that support: (i) firm entry by young firms and, through more effective exit procedures, a more effective resource reallocation across and towards the most productive firms; (ii) more effective flows/transfers of knowledge, managerial practices and technology flows across firms through denser networks; (iii) stronger firm capabilities, by fostering improvements in firm internal processes and productivity.

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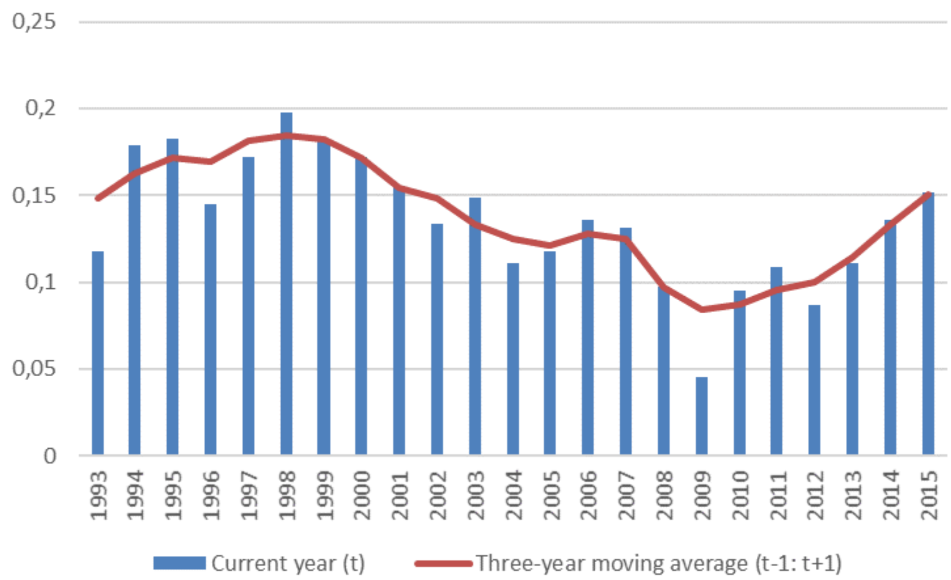
Tables and Figures

Figure 1

The 90th percentile of the employment growth rate distribution



Notes: This figure plots the 90th percentile of the employment growth rate distribution, both on a year-on-year basis (year t) and by considering the three-year moving average (from *t-1* to *t+1*)

Figure 2

Spells of HG and NHG within a hypothetical firm *i;* the characteristics of the spells

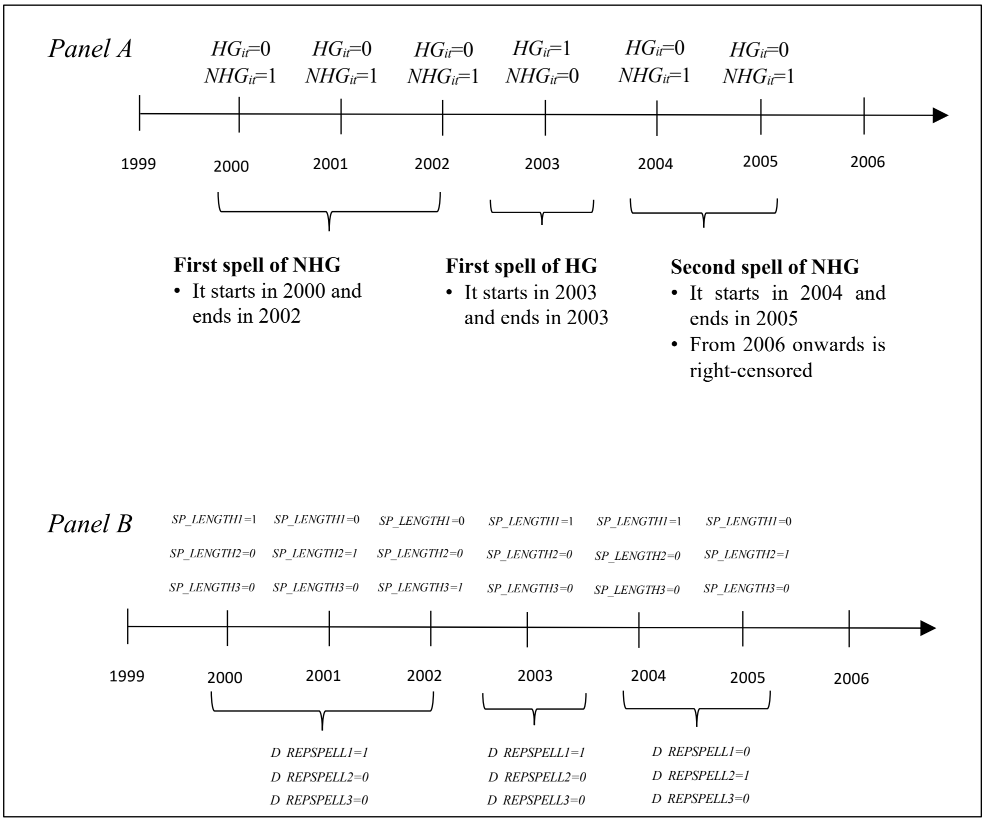


Figure 3 Spell length: average adjusted predictions for the three states (selected variables)

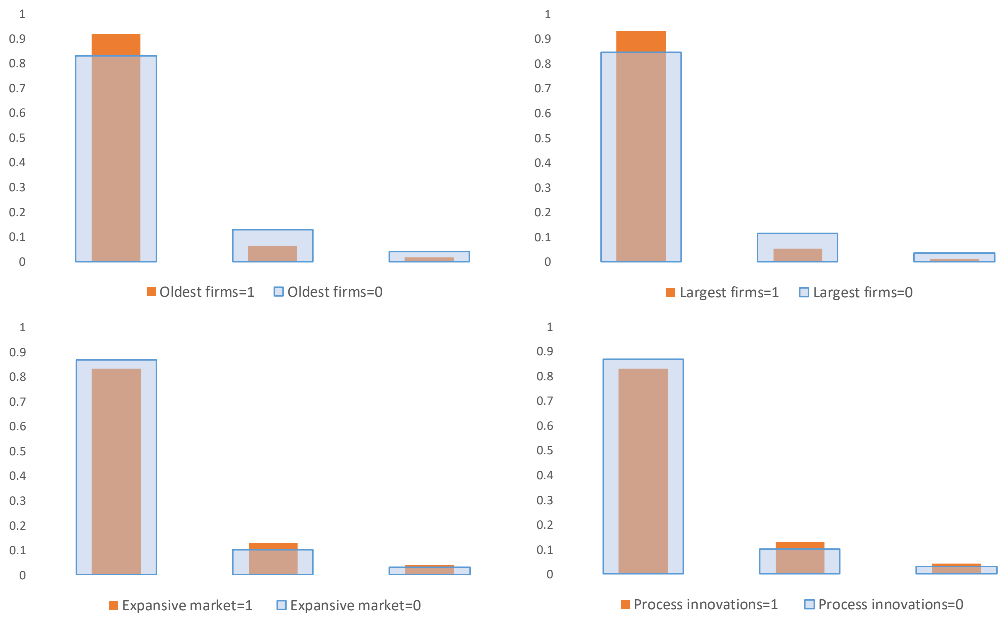


Table 1
Descriptive analysis of the spells of HG and NHG in the sample

	(1)	(2)	(3)	(4)
Length (in years)	NHG spells	HG spells	Maximum-length NHG spells (firms)	Maximum-length HG spells (firms)
1	21.56	85.70	13.55	80.39
2	18.57	11.33	15.47	15.18
3	12.85	2.01	11.23	3.00
4	10.72	0.56	11.81	0.84
5	8.37	0.28	10.16	0.42
6	6.38	0.11	7.81	0.16
7	4.84		6.53	
8	4.09		5.46	
9	4.03		5.72	
10	1.56		2.23	
11	1.46		2.09	
12	1.01		1.45	
13	0.79		1.13	
14	1.30		1.86	
15	0.57		0.81	
16	0.41		0.58	
17	0.67		0.96	
18	0.28		0.41	
19	0.16		0.23	
20	0.24		0.35	
21	0.12		0.17	
Total (%)	100.00	100.00	100.00	100.00
Total (frequency)	4934	2832	3446	1897
Observations=spell*year (frequency)	21585	3362		
Hazard rate = Probability of transition to the other state after 1 year in the initial state	0.10	0.76		

Table 2
Variables included in the analysis: definitions and descriptive statistics

Variable	Type	Definition	Mean	p25	p50	p75
Characteristics of the spells						
SP_LENGTH	Discrete (three binary variables)	Three binary variables are defined, which gather the spells which last, respectively, 1 year, 2 years or 3 years/more (i.e. no. of years in the current growth state).	See Table 1			
SP_REP	Discrete (three binary variables)	Three binary variables are defined, which gather the spells that are, respectively, the first spell, second spell and third or higher order repeated spell of the same type within the firm.	See Table 1			
Structural firm characteristics						
SIZE	Discrete (five binary variables)	Firms are classified into five groups in terms of the number of employees, where: (1):[10-20] employees; (2): [21-50] employees; (3): [51-200] employees; (4): [201-500] employees; (5): >500 employees. The size category is measured (and introduced in the empirical model) at the onset of the current spell.	217.5	19	45	192
AGE	Discrete (five binary variables)	Firms are classified into five groups in terms of the number of years since the firm establishment, where: (1): [0-5] years old; (2): [6-10] years old; (3): [11-20] years old; (4): [21-30] years old; (5): > 30 years old. The age category is measured (and introduced in the empirical model) at the onset of the current spell.	28.7	14	23	38
Productivity and innovation						
PRODUCTIVITY	Discrete (three binary variables)	Productivity is defined as the ratio between total sales (in euros) and the number of employees in year *t*. Three binary variables are built, which group, respectively: (L) those firms with a level of productivity lower than the 25th percentile of the sample productivity distribution in year *t*; (M) those firms which show a productivity level between the 25th and 75th percentile; (H) those firms whose productivity level is above the 75th percentile. Productivity categories are introduced in the empirical model as 1-year lagged to reduce simultaneity issues.	171140.3	66374.2	114281.5	197294.1
PROD_INN	Binary	It is a binary variable, which takes value equal to 1 if the firm introduced a product innovation in year *t*, 0 otherwise. It is introduced in the empirical model as 1-year lagged to reduce potential simultaneity issues.	0.198	0	0	1
PROC_INN	Binary	It is a binary variable, which takes value equal to 1 if the firm introduced a process innovation in year *t*, 0 otherwise. It is introduced in the empirical model as 1-year lagged to reduce potential simultaneity issues.	0.306	0	0	1
Alternative strategies for growth						
GROUP	Binary	It is a binary variable, which takes value equal to 1 if the firm is part of a industrial group, 0 otherwise. It is introduced in the empirical model as 1-year lagged to reduce potential simultaneity issues.	0.337	0	0	1
EXPORTER	Binary	It is a binary variable, which takes value equal to 1 if the firm exported (either directly or indirectly) in year *t*, 0 otherwise. It is introduced in the empirical model as 1-year lagged to reduce potential simultaneity issues.	0.640	0	1	1
Financial structure						
LEVERAGE	Discrete (three binary variables)	Leverage is defined as the ratio between total debts and the sum of total debts and shareholders' equity in year *t*. Three binary variables are built, which group, respectively: (L) those firms with a leverage ratio lower than the 25th percentile of the sample leverage distribution in year *t;* (M) those firms which show a leverage ratio between the 25th and 75th percentile; (H) those firms whose leverage level is ratio above the 75th percentile. Leverage categories are introduced in the empirical model as 1-year lagged to reduce simultaneity issues.	0.240	0.045	0.195	0.393
Market and demand characteristic						
MARKETDYN	Discrete (three binary variables)	Three binary variables are built, which group, respectively: (R/1) firms that declare that their principal market is going through a recessive phase; (S/2) firms that declare their principal market is stable; (E/3) firms that declare their principal market is passing through an expansive phase. The three dummies are introduced in the empirical model as 1-year lagged to reduce simultaneity issues.	1.91	1	2	2
MARKETSH	Discrete (three binary variables)	Three binary variables are built, which group, respectively: (D/1) firms that declare that their market share is shrinking; (S/2) firms that declare that their market share is stable; (E/3) firms that declare that their market share is growing. The three dummies are introduced in the empirical model as 1-year lagged to reduce simultaneity issues.	1.99	1	2	2

Table 3

Main results: random effects logit model estimates of NHG and HG hazard rates. Separate regressions.

	(1) NHG hazard (NHG to HG)	(2) HG hazard (HG to NHG)
Determinants		
Characteristics of the spells		
SP_LENGTH$_2$	1.016	0.750*
	(0.081)	(0.125)
SP_LENGTH$_3$	0.996	0.389***
	(0.079)	(0.115)
SP_REP$_2$	0.920	1.087
	(0.087)	(0.110)
SP_REP$_3$	0.605***	1.209
	(0.105)	(0.332)
Year dummies		
Year: 1995	0.646	1.172
	(0.190)	(0.305)
Year: 1996	0.816	1.025
	(0.227)	(0.282)
Year: 1997	1.070	0.998
	(0.281)	(0.267)
Year: 1998	0.747	0.628*
	(0.196)	(0.151)
Year: 1999	0.824	1.333
	(0.217)	(0.362)
Year: 2000	0.739	0.952
	(0.194)	(0.247)
Year: 2001	0.798	1.009
	(0.207)	(0.260)
Year: 2002	0.981	0.628*
	(0.252)	(0.162)
Year: 2003	0.714	1.675*
	(0.192)	(0.478)
Year: 2004	0.791	0.788
	(0.210)	(0.223)
Year: 2005	1.012	0.800
	(0.268)	(0.225)
Year: 2006	0.867	1.542
	(0.220)	(0.414)
Year: 2007	0.695	0.917
	(0.177)	(0.226)
Year: 2008	0.363***	1.037
	(0.098)	(0.266)
Year: 2009	0.790	0.745
	(0.201)	(0.212)
Year: 2010	0.917	1.085
	(0.233)	(0.271)
Year: 2011	0.457***	0.842
	(0.121)	(0.204)
Year: 2012	0.655	0.948
	(0.171)	(0.270)
Year: 2013	0.756	0.814
	(0.195)	(0.211)
Year: 2014	0.755	1.034
	(0.198)	(0.275)
Industry dummies		
Industry: Food and tobacco	1.283	1.010
	(0.239)	(0.260)
Industry: Beverages	0.894	0.955
	(0.257)	(0.403)
Industry: Textiles and clothing	0.802	1.030
	(0.159)	(0.284)
Industry: Leather, fur and footwear	1.608	0.955
	(0.357)**	(0.289)
Industry: Timber	1.495	0.722
	(0.324)*	(0.211)
Industry: Paper	0.716	1.096
	(0.170)	(0.368)
Industry: Printing and publishing	0.650	1.672
	(0.149)*	(0.611)
Industry: Chemicals	0.696	0.668
	(0.149)*	(0.191)
Industry: Plastic and rubber products	1.145	0.781
	(0.234)	(0.215)
Industry: Non-metal mineral products	0.891	0.789
	(0.181)	(0.220)
Industry: Basic metal products	0.619	0.698
	(0.153)*	(0.236)
Industry: Fabricated metal products	0.934	0.971
	(0.172)	(0.247)

Industry: Industrial and agricultural equipment	0.756	0.870
	(0.160)	(0.248)
Industry: Office mach., data proc., precision instr. and similar	0.762	0.659
	(0.195)	(0.226)
Industry: Electric materials and accessories	0.796	0.630
	(0.176)	(0.183)
Industry: Vehicles and motors	0.838	0.932
	(0.178)	(0.277)
Industry: Other transport equipment	0.924	0.605
	(0.245)	(0.205)
Industry: Furniture	1.133	0.939
	(0.235)	(0.266)
Industry: Miscellaneous	1.143	0.801
	(0.283)	(0.268)
Constant	0.111***	3.600***
	(0.032)	(1.056)
Ln variance of the firm random effects (lnsig2u)	0.593	0.042
	(0.147)**	(0.170)
Observations	21585	3362

Notes:
Transitions explained by the duration and order (repetition) of the current spell, year- and industry (2-digit level, NACE-rev.2) effects and firm unobserved heterogeneity. All the coefficients in the table are exponentiated and are interpreted as hazard ratios with respect to the baseline (omitted) category. Standard errors in brackets. Statistical significance at the 10%, 5% and 1% level is indicated by *, ** and ***, respectively.

Table 4

Main results: random effects logit model estimates of NHG and HG hazard rates. Separate regressions

	(1) NHG hazard (NHG to HG)	(2) HG hazard (HG to NHG)
Determinants		
Characteristics of the spells		
SP_LENGTH_2	1.059	0.791
	(0.087)	(0.130)
SP_LENGTH_3	1.082	0.454***
	(0.087)	(0.130)
SP_REP_2	0.923	1.037
	(0.083)	(0.109)
SP_REP_3	0.621***	1.161
	(0.099)	(0.330)
Structural firm characteristics		
AGE_2	0.918	1.375**
	(0.097)	(0.219)
AGE_3	0.743***	1.524***
	(0.072)	(0.226)
AGE_4	0.593***	1.382*
	(0.066)	(0.229)
AGE_5	0.469***	1.944***
	(0.053)	(0.335)
$SIZE_2$	0.828**	1.349***
	(0.065)	(0.153)
$SIZE_3$	0.574***	1.253*
	(0.058)	(0.172)
$SIZE_4$	0.363***	1.510**
	(0.050)	(0.279)
$SIZE_5$	0.276***	1.366
	(0.050)	(0.313)
Productivity and innovation		
$PRODUCTIVITY_M$	1.357***	0.808*
	(0.103)	(0.090)
$PRODUCTIVITY_H$	1.827***	0.585***
	(0.191)	(0.086)
PROD_INN	0.865*	0.874
	(0.070)	(0.098)
PROC_INN	1.250***	0.923
	(0.081)	(0.087)
Alternative strategies for growth		
GROUP	0.807**	0.743**
	(0.070)	(0.088)
EXPORTER	0.852**	1.109
	(0.061)	(0.114)
Financial structure		
$LEVERAGE_M$	0.957	1.021
	(0.069)	(0.116)
$LEVERAGE_H$	1.048	0.796*
	(0.087)	(0.100)
Market and demand characteristic		
$MARKETDYN_S$	1.381***	0.864
	(0.116)	(0.126)
$MARKETDYN_E$	1.741***	0.650***
	(0.175)	(0.105)
$MARKETSH_S$	1.075	1.159
	(0.096)	(0.181)
$MARKETSH_E$	1.438***	1.159
	(0.152)	(0.200)
Constant	0.093***	3.754***
	(0.029)	(1.368)
Year dummies	Yes	Yes
Industry dummies	Yes	Yes
Ln variance of the firm random effects	0.523**	0.026
	(0.132)	(0.165)
Observations	20610	3261

Notes:
Transitions explained by firm and market (demand) characteristics, the duration and order (repetition) of the current spell, year- and industry (2-digit level, NACE-rev.2) effects and firm unobserved heterogeneity. All the coefficients in the table are exponentiated and are interpreted as hazard ratios with respect to the baseline (omitted) category. Standard errors in brackets. Statistical significance at the 10%, 5% and 1% level is indicated by *,** and ***, respectively.
Coefficients of the year and industry dummies are not reported to save space. Full tables are available from authors upon requests.

Table 5

Further results: the Great Recession. Random effects logit model estimates of NHG and HG hazard rates. Separate regressions.

	NHG hazard (NHG to HG)		
	(1) Hazard ratios with respect to the baseline (omitted) category <=2007	(2) Interactions = $D\_DOWNTURN{*}X_i$	(3)=(1)*(2) Hazard ratios with respect to the baseline (omitted) category >=2008 Calculated only when the interaction is significant
D_DOWNTURN	0,620		
	(0.194)		
AGE_2	0.858	1.663*	1.427
	(0.101)	(0.450)	
AGE_3	0.761***	1.419	*Equal to <=2007*
	(0.079)	(0.355)	
AGE_4	0.572***	1.631*	0.933
	(0.073)	(0.431)	
AGE_5	0.414***	1.940**	0.803
	(0.054)	(0.509)	
$SIZE_2$	0.726***	1.432**	1.040
	(0.069)	(0.211)	
$SIZE_3$	0.599***	1.002	*Equal to <=2007*
	(0.076)	(0.185)	
$SIZE_4$	0.379***	1.048	*Equal to <=2007*
	(0.064)	(0.261)	
$SIZE_5$	0.267***	1.249	*Equal to <=2007*
	(0.059)	(0.416)	
PROC_INN	1.192***	1.101	*Equal to <=2007*
	(0.098)	(0.142)	
GROUP	0.900	0.841	*Equal to <=2007*
	(0.103)	(0.137)	
Year and Industry dummies	Yes		
Observations	20610		

	HG hazard (HG to NHG)		
	(4) Hazard ratios with respect to the baseline (omitted) category <=2007	(5) Interactions = $D\_DOWNTURN{*}X_i$	(6)=(4)*(5) Hazard ratios with respect to the baseline (omitted) category >=2008 Calculated only when the interaction is significant
D_DOWNTURN	1.772		
	(1.265)		
AGE_2	1.309	0.989	*Equal to <=2007*
	(0.216)	(0.686)	
AGE_3	1.525***	0.739	*Equal to <=2007*
	(0.239)	(0.486)	
AGE_4	1.427*	0.734	*Equal to <=2007*
	(0.269)	(0.490)	
AGE_5	2.359***	0.532	*Equal to <=2007*
	(0.467)	(0.355)	
$SIZE_2$	1.392**	0.823	*Equal to <=2007*
	(0.190)	(0.196)	
$SIZE_3$	1.197	1.006	*Equal to <=2007*
	(0.205)	(0.282)	
$SIZE_4$	1.429	0.923	*Equal to <=2007*
	(0.324)	(0.351)	
$SIZE_5$	1.138	1.654	*Equal to <=2007*
	(0.305)	(0.835)	
PROC_INN	0.824*	1.460*	1.203
	(0.094)	(0.294)	
GROUP	0.634***	1.517*	0.961
	(0.094)	(0.370)	
Year and Industry dummies	Yes		
Observations	3261		

Notes:
Transitions explained by firm and market (demand) characteristics, the duration and order (repetition) of the current spell, industry (2-digit level, NACE-rev.2) effects, the phase of the business cycle (*D_DOWNTURN=1* for the period 2008-2014) and firm unobserved heterogeneity. All the coefficients in the table are exponentiated and are interpreted as hazard ratios with respect to the baseline (omitted) category. Standard errors in brackets. Statistical significance at the 10%, 5% and 1% level is indicated by *,** and ***, respectively. Only a sub-set of coefficients with significant interaction with the dummy capturing the phase of the business cycle has been reported to save space. Full tables are available from authors upon requests.

Table 6 Further results: length and repetition of HG spells

# years / # repetitions	(1) HG spell length (# spells)	% (spells)	(2) HG spell repetition (# firms)	% (firms)
1	2151	85.5	1019	64.4
2	282	11.2	393	24.9
3 or more	84	3.3	170	10.7
Total	2517	100	1582	100

Table 7 Marginal effects on the length of HG spells (selected variables)

	HG spell length		
	1 year	2 years	3 years or more
AGE_5	0.088	-0.065	-0.023
$SIZE_5$	0.085	-0.063	-0.021
$MARKETDYN_E$	-0.036	0.026	0.010
PROC_INN	-0.038	0.027	0.011

Table 8

Robustness check (i): (real) sales as proxy for firm size. Random effects logit model estimates of NHG and HG hazard rates.

	(1)	(2)
	NHG hazard (NHG to HG)	HG hazard (HG to NHG)
Determinants		
Characteristics of the spells		
SP_LENGTH_2	1.130	0.803*
	(0.091)	(0.099)
SP_LENGTH_3	1.082	0.436***
	(0.087)	(0.085)
SP_REP_2	1.019	1.033
	(0.093)	(0.107)
SP_REP_3	0.995	1.158
	(0.149)	(0.320)
Structural firm characteristics		
AGE_2	0.915	1.363**
	(0.102)	(0.215)
AGE_3	0.725***	1.518***
	(0.074)	(0.222)
AGE_4	0.638***	1.387**
	(0.073)	(0.226)
AGE_5	0.675***	1.937***
	(0.075)	(0.325)
$SIZE_2$	0.871*	1.360***
	(0.073)	(0.151)
$SIZE_3$	0.646***	1.260*
	(0.066)	(0.170)
$SIZE_4$	0.553***	1.511**
	(0.071)	(0.275)
$SIZE_5$	0.493***	1.369
	(0.080)	(0.307)
Productivity and innovation		
$PRODUCTIVITY_M$	0.652***	0.825*
	(0.049)	(0.090)
$PRODUCTIVITY_H$	0.458***	0.610***
	(0.051)	(0.087)
PROD_INN	0.880	0.885
	(0.069)	(0.097)
PROC_INN	1.234***	0.936
	(0.079)	(0.088)
Alternative strategies for growth		
GROUP	1.207**	0.733***
	(0.099)	(0.085)
EXPORTER	1.218***	1.095
	(0.090)	(0.111)
Financial structure		
$LEVERAGE_M$	1.020	1.016
	(0.072)	(0.114)
$LEVERAGE_H$	1.157*	0.808*
	(0.096)	(0.100)
Market and demand characteristic		
$MARKETDYN_S$	1.144*	0.877
	(0.090)	(0.127)
$MARKETDYN_E$	1.429***	0.656***
	(0.137)	(0.104)
$MARKETSH_S$	1.170*	1.143
	(0.098)	(0.177)
$MARKETSH_E$	1.300**	1.133
	(0.134)	(0.194)
Constant	0.076***	3.637***
	(0.027)	(1.306)
Year dummies	Yes	Yes
Industry dummies	Yes	Yes
Ln variance of the firm random effects	0.571**	0.000
	(0.137)	(0.003)
Observations	20456	3276

Notes:
Transitions explained by firm and market (demand) characteristics, the duration and order (repetition) of the current spell, year- and industry (2-digit level, NACE-rev.2) effects and firm unobserved heterogeneity. All the coefficients in the table are exponentiated and are interpreted as hazard ratios with respect to the baseline (omitted) category. Standard errors in brackets. Statistical significance at the 10%, 5% and 1% level is indicated by *,** and ***, respectively.
Coefficients of the year and industry dummies are not reported to save space. Full tables are available from authors upon requests.

Table 9

Robustness check (ii): Multilevel two-state logit model estimates of NHG and HG hazard rates. Joint estimation.

	(1) NHG hazard (NHG to HG)	(2) HG hazard (HG to NHG)
Determinants		
Characteristics of the spells		
SP_LENGTH_2	1.061	0.824
	(0.086)	(0.103)
SP_LENGTH_3	1.087	0.489***
	(0.075)	(0.098)
SP_REP_2	0.947	1.124
	(0.068)	(0.122)
SP_REP_3	0.681***	1.298*
	(0.077)	(0.203)
Structural firm characteristics		
AGE_2	0.921	1.372*
	(0.097)	(0.222)
AGE_3	0.742***	1.510***
	(0.071)	(0.228)
AGE_4	0.592***	1.402**
	(0.064)	(0.236)
AGE_5	0.471***	1.964***
	(0.051)	(0.340)
$SIZE_2$	0.824**	1.388***
	(0.064)	(0.158)
$SIZE_3$	0.565***	1.319**
	(0.056)	(0.183)
$SIZE_4$	0.358***	1.630***
	(0.048)	(0.304)
$SIZE_5$	0.266***	1.490*
	(0.047)	(0.342)
Productivity and innovation		
$PRODUCTIVITY_M$	1.357***	0.792**
	(0.102)	(0.089)
$PRODUCTIVITY_H$	1.826***	0.557***
	(0.187)	(0.082)
PROD_INN	0.870*	0.857
	(0.071)	(0.096)
PROC_INN	1.251***	0.920
	(0.081)	(0.088)
Alternative strategies for growth		
GROUP	0.813**	0.742**
	(0.070)	(0.089)
EXPORTER	0.854**	1.115
	(0.061)	(0.116)
Financial structure		
$LEVERAGE_M$	0.958	1.003
	(0.069)	(0.115)
$LEVERAGE_H$	1.051	0.787*
	(0.087)	(0.100)
Market and demand characteristic		
$MARKETDYN_S$	1.386***	0.863
	(0.116)	(0.127)
$MARKETDYN_E$	1.754***	0.646***
	(0.175)	(0.104)
$MARKETSH_S$	1.071	1.167
	(0.095)	(0.184)
$MARKETSH_E$	1.428***	1.169
	(0.151)	(0.203)
Constant	0.093***	3.793***
	(0.029)	(1.393)
Year dummies	Yes	Yes
Industry dummies	Yes	Yes
Variance of the firm random effects	1.690***	1.105***
	(0.000)	(0.000)
Covariance of the firm random effects	0.795***	
	(0.000)	
Observations	23871	

Notes:
The equations modeling the two types of transitions are allowed to have a not independent error structure. Transitions explained by firm and market (demand) characteristics, the duration and order (repetition) of the current spell, year- and industry (2-digit level, NACE-rev.2) effects and firm unobserved heterogeneity. All the coefficients in the table are exponentiated and are interpreted as hazard ratios with respect to the baseline (omitted) category. Standard errors in brackets Statistical significance at the 10%, 5% and 1% level is indicated by *,** and ***, respectively. Coefficients of the year and industry dummies are not reported to save space.
Full tables are available from authors upon requests.

A.1 Generalized ordered logit model

Table A.1 Generalized ordered logit model: length and repetition of HG spells

	(1)	(2)
Determinants	HG spell length	Repetition of HG spells
Structural firm characteristics		
AGE_2	-0.471**	2.019***
	(0.224)	(0.421)
AGE_3	-0.728***	2.447***
	(0.210)	(0.405)
AGE_4	-0.767***	2.528***
	(0.243)	(0.412)
AGE_5	-1.182***	2.272***
	(0.240)	(0.413)
$SIZE_2$	-0.446***	0.209
	(0.162)	(0.147)
$SIZE_3$	-0.449**	0.021
	(0.204)	(0.181)
$SIZE_4$	-0.740***	-0.367
	(0.274)	(0.232)
$SIZE_5$	-0.957**	-0.146
	(0.385)	(0.299)
Productivity and technology effort		
$PRODUCTIVITY_M$	0.196	-0.068
	(0.158)	(0.137)
$PRODUCTIVITY_H$		-0.201
		(0.197)
$PRODUCTIVITY_H$ (1 vs 2&3)	0.351*	
	(0.211)	
$PRODUCTIVITY_H$ (1&2 vs 3)	1.112***	
	(0.286)	
PROD_INN	0.041	-0.249
	(0.174)	(0.153)
PROC_INN	0.363**	0.049
	(0.146)	(0.126)
Alternative strategies for growth		
GROUP	0.078	-0.038
	(0.179)	(0.159)
EXPORTER	0.104	0.110
	(0.146)	(0.133)
Financial structure		
$LEVERAGE_M$	0.109	-0.099
	(0.168)	(0.142)
$LEVERAGE_H$	0.288	-0.086
	(0.181)	(0.163)
Market and demand characteristic		
$MARKETDYN_S$	0.283	-0.055
	(0.205)	(0.162)
$MARKETDYN_E$	0.413*	0.099
	(0.214)	(0.192)
$MARKETSH_S$	-0.022	0.059
	(0.219)	(0.185)
$MARKETSH_E$	0.291	-0.235
	(0.231)	(0.216)
Constant *(1 vs 2&3)*	-1.729***	2.269***
	(0.579)	(0.535)
Constant *(1&2 vs 3)*	-3.612***	3.879***
	(0.585)	(0.540)
Year dummies	Yes	Yes
Industry dummies	Yes	Yes
Observations	2445	1532

Notes:
Coefficients of year and industry dummies are not reported to save space. Standard errors in brackets Full tables are available from authors upon requests. Statistical significance at the 10%, 5% and 1% level is indicated by *,** and ***, respectively.