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RESEARCH ARTICLE

Coping with high decline: firms' resilience to adversity

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Abstract This work investigates the factors that precipitate a firm's sudden high decline, which is defined as a short-term heavy contraction in firm size, and examines firms' performance in the aftermath of a high-decline (HD) event. The empirical analysis reveals patterns of HD events over the business cycle and across markets, providing insights into the factors that enable firms' resilience in terms of better growth performance after an HD event. Firms that upgrade their production processes and invest in enhancing their human capital show better growth trajectories in the aftermath of an HD event.

Plain English Summary Periods of high decline are times of challenge and opportunity. This paper studies the drivers of a firm's sudden decline episodes and uncovers its strategic choices that boost its resilience to them. A key implication of this study is that process innovation and human capital effectively reduce a firm's risk of HD and improve its fate after such a high decline. Our findings may be particularly relevant for young SMEs, which may benefit from support policies that help them weather such periods of high decline.

Keywords High-decline events · Business cycle · Resilience · Productivity · Growth trajectories

JEL Classification D22 · D23 · L25 · L60

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1 Introduction

Many businesses face periods of decline during their life cycle. These challenging periods usually lead to reductions in a firm's size and resources (Whetten, 1987). Such decline events may be the result of external shocks to the firm, which occur at different levels of disaggregation. Widespread macroeconomic downturns (e.g., those related to the Great Recession or the COVID-19 pandemic) heavily impact active firms in a country (Mina and Santoleri, 2021). Specific markets may react differently to the same macro shock (Bamiatzi and Kirchmaier, 2014), thus providing businesses with differing prospects of growth or decline. Finally, idiosyncratic shifts in a firm's demand, which are conditional on such macro- and market-level dynamics, reveal micro-heterogeneity in the effects of such shocks on its performance (Pozzi and Schivardi, 2016). In the face of declining events, firms are not passive spectators, and they have a wide range of strategic choices. They may rely on internal capabilities and strategic resources (Barney and Arikan, 2002; Arrighetti et al. 2021) to resume a trajectory of stability and growth. A firm's strategy includes actions and investments in both tangible and intangible assets that enhance its efficiency, improve the skills of its employees, and increase its customer base. Alternatively, if the endowment of capabilities and strategic resources is poor or no action is taken, the firm may further decline until its exit from the market becomes inevitable (Starbuck et al., 1978).

Previous studies have analyzed the consequences of periods of macroeconomic downturns on the contemporaneous growth rates of firms (Fort et al., 2013; Criscuolo et al., 2014; Mina and Santoleri, 2021; Arrighetti et al. 2021) and the characteristics that make them resilient to shocks and increase their chances of survival (Battisti et al., 2019; Landini et al., 2020). Moreover, other studies have analyzed firms' growth paths (i.e., medium- and long-term growth trajectories) in "normal times" (McMahon, 2001; Garnsey and Heffernan, 2005; Garnsey et al., 2006; McKelvie and Wiklund, 2010; Coad et al., 2013; Dosi et al., 2020). Notwithstanding, the extant literature has seldom focused on the role that decline events play in firms' subsequent responses and growth trajectories. Indeed, to our knowledge, only a few studies have examined the specific relationship between downsizing and bankruptcy (Powell and Yawson, 2012; Zorn et al., 2017), while no previous work has enquired into firms' strategic choices and their multiple alternative growth trajectories in the face of decline. We believe it is important to increase the knowledge about the factors that help a firm to return to a sustainable path in the face of a high decline (HD, hereafter) event.

To fill this gap, this paper investigates the determinants of three alternative growth trajectories that a firm may follow in the face of a sudden HD event: *fast growth*, *moderate positive or negative growth,* and *exit from the market*. HD events are defined as heavy short-term (i.e., one year) contractions in the number of employees, which makes a firm fall to the lowest decile of the sample distribution of employment growth rates. In focusing on HD events, we examine cases of significant falls in performance and reduce the risk of capturing either temporary small fluctuations in a firm's size or mere noise.

We use a dataset comprising a large sample of Spanish manufacturing firms of different age and size classes observed over 15 years (2001–2016). The sample period includes both the remarkable expansion of the Spanish economy and the Great Recession. The multi-scope nature of the survey used in this study allows us to assess the role of several supply-side and demand-side factors that could affect both the likelihood of an HD event and the growth trajectory followed by a firm after suffering such an event.

This paper makes two major contributions to the literature. First, it contributes to the comprehension of factors that cause a firm's decline by focusing on occurrences of heavy contractions in firm size. In this respect, a study of the events located in the left tail of the growth rate distribution, both their occurrence and determinants, over the business cycle and across markets, may inform managers and policymakers regarding the factors that precipitate a firm's sudden decline. Second, this paper adds to the emerging literature on growth paths by examining the growth trajectories of firms following an HD event and identifying factors that help firms to resume stability or growth after such an event. Our analysis emphasizes the relevance of the decisions taken by managers, entrepreneurs, and policymakers in that context.

Three main results emerge from our study. First, while most HD events occurred during the period 2008–2013 when a major macroeconomic downturn took place, several supply-side determinants, such as the level of productivity and investments in human and physical capital, are important in reducing a firm's risk of facing an abrupt decline. In addition to these supply-side variables, a firm's likelihood of experiencing an HD event is related to the dynamics of both the market in which it is active and its market share. The latter points towards the relevance of idiosyncratic demand-side factors in shaping the probability of the occurrence of HD events and should lead a firm to put in action strategies for building a broad and solid customer base and enhancing a firm's reputation. Second, after experiencing an HD event, several strategic actions by the firm, such as process innovation, investment in human and physical capital, and reduction of financial leverage levels, are significantly and positively associated with the likelihood of a rapid growth trajectory versus a moderate growth trajectory, or even market exit. Third, the probabilities associated with growth trajectories differ between firms that have experienced an HD event and those that have not. Furthermore, while most factors that contribute to long-term growth play similar roles for these two groups of firms, process innovation and the expansionary dynamics of the firm's market share significantly increase the likelihood of a positive growth trajectory after undergoing an HD event.

The rest of this paper is organized as follows. We first review the related literature and clarify the main contributions of our paper. In Section 3, we describe the dataset, outline the reference model that guides the empirical analysis, and provide preliminary evidence of the patterns of occurrence of HD events over the business cycle. Section 4 briefly outlines the stages of the econometric analysis and presents and discusses our main empirical findings regarding (i) the determinants of HD, and (ii) the likelihood and determinants of three growth trajectories that may occur in the aftermath of an HD event. We include a counterfactual analysis to assess whether the trajectories differ between firms that have experienced an HD event and those that have not. Section 5 presents and discusses some further results and robustness checks. Finally, in Section 6, we present the main conclusions of the paper and discuss implications for both managers and policymakers.

2 Related literature

This section provides a brief overview of the related literature to clarify the main contributions of the paper. We relate these to the five strands of the extant literature presented below.

2.1 HD events and the nature of the firm

The existing literature on firm dynamics has shown that firm growth and decline are not "smooth" processes. While most firms do not significantly change their size in a year, the most interesting growth events occur as lumps and bumps. Particular attention should therefore be paid to the (extreme) episodes in the tails of the growth rate distribution. These episodes have been associated with different factors, such as the occurrence of radical innovations (Arata, 2019), the consideration of the firm as a bundle of discrete resources (Penrose, 1959), organizational slacks (Coad et al., 2022; Coad, 2022) and the existence of growth thresholds due to specific taxes and labor market regulations (Garicano et al., 2016).

However, while previous papers have focused on the far-right tail, where high-growth (HG) occurs (Schreyer, 2000; Dosi et al., 2020; Esteve-Pérez et al., 2022), firm decline and the events in the left tail of the growth rate distribution have been largely overlooked (Storey, 2011; Coad et al., 2014).[1] Hence, the study of the events located in the left tail of the growth rate distribution, their occurrence and determinants, both in the business cycle and across markets, is deemed important as it could inform both managers and policymakers about the factors that precipitate a firm's sudden decline.

This paper contributes to the literature on firm growth through the investigation of factors associated with a firm's abrupt decline by focusing on occurrences of high decline (HD) events. We define HD as a heavy short-term (i.e., one year) contraction in the number of employees, which causes the firm to fall to the lowest decile of the sample distribution of employment growth rates. The reader is cross-referred to Section 3.2 for the operational definition of an HD event.

2.2 HD events, downsizing, and firm exit

HD is different from exit, which occurs when a firm leaves the market (Cefis et al., 2022). Instead, firm decline relates to challenging periods that lead to reductions in a firm's size and resources (Whetten, 1987). More specifically, HD can be the result of a

[1] An interesting exception is the work by Goedhuys and Sleuwaegen (2016), in which the authors assessed the effects of human capital and R&D activities on the probability that a firm would experience either a HG or an HD event based on a small panel dataset of firms located in the Flemish and Brussels' Capital Regions in Belgium.

deliberate choice by firms to focus on downsizing and core competencies, or the result of external adverse shocks. Downsizing could be a strategic choice to reduce the size and regain competitiveness by building a lean organization (Datta et al., 2010). In this respect, downsizing and decline are different concepts (Freeman and Cameron, 1993) that should be kept separate, at least in theory.[2]

In the face of a decline, firms may rely on internal capabilities and strategic resources (Barney and Arikan, 2002; Arrighetti et al., 2021) to resume a path of stability and growth. Alternatively, if the endowment of capabilities and strategic resources is poor or no action is taken, the firm may further decline until exit from the market becomes inevitable (Starbuck et al., 1978). In this sense, a firm's decline may (though not necessarily) be a prelude to its exit: companies that experience an HD event may or may not exit the market after that event.

This paper relates to the organizational literature on the corporate decline (Hambrick and D'Aveni, 1988; Freeman and Cameron, 1993; Wiseman and Bromiley, 1996). Most previous studies on decline have focused on selected groups of firms, either large and listed corporations (Hambrick and D'Aveni, 1988; Zorn et al., 2017), selected industries (Gittel et al., 2006), a relatively small sample of firms (Wiseman and Bromiley, 1996), or case studies (Redman and Keithley, 1998). Unlike these studies, we carry out a comprehensive analysis of the determinants of a firm's "setback" based on a large sample of firms of a wide range of sizes and age classes.

Furthermore, our paper speaks to the literature that has focused on the steady decline in the performance of firms several years before exit ("shadow of death" effect) and on "zombie" firms (Carreira and Teixeira, 2011; Schivardi et al., 2022; Carreira et al., 2022). While this literature has highlighted the role of barriers to firm mobility in promoting the delayed exit of unproductive and debt-ridden firms, we take a complementary perspective and focus on the episodes of a sudden and rapid decline of firms before their eventual exit (vs other possible fates). Policymakers are particularly interested in these episodes, because of their great impact on job destruction. Indeed, size reduction by incumbent old firms was a major factor behind the large drop in aggregate employment during the Great Recession (Criscuolo et al., 2014). In this respect, while the labor economics literature has examined the consequences of mass layoffs for workers' earnings and career losses (Blien et al., 2021), in the second part of the empirical analysis we look at the consequences of severe employment reductions for the subsequent firms' performance.

2.3 Productivity dynamics, HD events, and the business cycle

Standard models of firm dynamics (Jovanovic, 1982; Hopenhayn, 1992) put forward that productivity is the key driver of firm dynamics, that is, the entry, growth, decline, and exit of firms. In these models, firm growth is a function of the *level* of productivity (and, in some contributions, also of the *change* in productivity, i.e., investments and innovation; Ericson and Pakes, 1995) and the size of the firm at the beginning of the period. Firm growth is caused by firms' responses to productivity positive shocks, while firm decline (or exit) is driven by firms' responses to productivity negative shocks.[3] The productivity-growth relationship is also at the core of Schumpeterian evolutionary models (Silverberg et al. 1988; Dosi et al., 1995), which predict a positive association between a firm's growth and its efficiency. In a replicator dynamic framework, firms with productivity higher than the industry average should grow more than the average firm in the industry, that is, should increase their market shares.

In this paper (see Section 4.1, and further explored in Section 4.3), we add to these strands of literature in industry dynamics, by adopting an empirical

[2] Because of data limitations (see Section 3), we cannot operationally distinguish downsizing from decline. Thus, we refer throughout the paper to (high) decline, but we acknowledge that these events may include intentional (heavy) downsizing. However, downsizing is a pervasive strategy in large corporations, but it is less evident in the SMEs' "toolkit". Given that the sample of Spanish manufacturing firms under analysis is mostly made up of micro and small firms, our results should mostly refer to decline episodes.

[3] Decker et al. (2020) have shown that responsiveness of firm growth to firm productivity has declined during the period 1981-2013 in both manufacturing and private sector US economy. The authors suggest that rising factor adjustment costs and firms' market power may be potential candidates to explain the observed fall in responsiveness.

specification in which, for a certain firm, the probability of experiencing an HD event is a function (among other things) of both the *level* of productivity and several proxies of productivity *change*, such as the introduction of product and process innovations, and investments in human and physical capital. In this way, while the *level* of productivity likely reflects relevant idiosyncratic features of the firm such as operational routines, human resources, and managerial practices, improvements (*changes*) in firm productivity may well be captured by process innovations and investments in physical and/or human capital. In the empirical model, we test the relationship between productivity and firm decline by introducing it either as an absolute measure or (in some specifications) as relative to the yearly average of the sector in which the firm is active (Domini and Moschella, 2022). By doing so, we aim to capture the effect of productivity on the probability of experiencing an HD event, gross and net of shocks that are common to all active firms in a sector in a certain year.

While these models focus on the long-run relationship between productivity and firm dynamics, the Great Recession and, more recently, the economic downturn due to COVID-19, have renewed the interest of both scholars and policymakers in how firms are affected by crises.[4] Beyond the overall negative effect of downturns, the literature has looked specifically at the *cleansing hypothesis* (Schumpeter, 1939; Caballero and Hammour, 1994; Foster et al., 2016), which suggests that a recession is a time of accelerated productivity-enhancing resource reallocation. Indeed, during crises, the role of productivity for firm growth and survival is even more crucial due to increased competitive pressures. Firms producing with outdated technologies are swiped out of the market and replaced by more productive producers. Previous empirical papers have shown that the enhanced reallocation during recessions is mainly driven by a sharp increase in job destruction and a mild decrease in job creation (Davis and Haltiwanger, 1999).

However, some authors (e.g., Foster et al., 2016) have cast some doubts about the increased (productivity-enhancing) reallocation effect of the Great Recession when compared to previous recessions. They argue that credit constraints may have left less relevance for market fundamentals (i.e., demand, productivity, and costs). Thus, the cleansing effect of the Great Recession may have been partly offset for several reasons. First, in the case of credit market imperfections, the most productive firms may be the most hit by the recession, due to their higher external finance need (Barlevy, 2003). Second, the destruction of infant (and potentially superior) businesses, which are probably more financially constrained, "scars" the economy during recessions and pulls average productivity down (Ouyang, 2009). Third, during a crisis, firms driven out of business may not be necessarily the least productive, but those more vulnerable to changing conditions in terms of access to credit or those more exposed to binding labor market regulations (Hallward-Driemeier and Rijkers, 2013). Finally, government policies supporting firms during recessions may offset the reallocation gains from a recession (Kozeniauskas et al., 2022).[5]

A contribution of this paper to this strand of the literature is that we do not assume a single and common-in-time negative shock faced by all firms (i.e., the Great Recession), but we spot firm-year-specific HD events. More specifically, we take advantage of the length of our sample period (i.e., 2001-2016) to place HD events along the different phases of the business cycle. The period considered comprises both upturn and downturn periods. Yet, we must bear in mind that, as previously underlined in Section 2.2, HD may not necessarily be a prelude to firm exit, but it may nonetheless lead to the reallocation of labor across firms (through a rapid and significant contraction in the number of employees) with potential effects on aggregate productivity.

We expect HD events to be more concentrated during a downturn than in an upswing. Moreover, we expect a significant role of productivity in lowering the chance of experiencing an HD episode, across all phases of the business cycle. However, based on the literature discussed above, it is unclear whether

[4] The literature has long investigated the relationship between the different phases of the business cycle and firm growth and decline. Geroski and Gregg (1993) found that a huge proportion of firms in the UK were severely affected in terms of sales and capacity by the recession in the early 1990s.

[5] Temporary employment maintenance mechanisms were relevant in the case of the COVID-19 crisis (e.g., the SURE program in the European Union), but that it was not the case in the Great Recession.

the negative relationship between productivity and decline becomes stronger in a crisis than in a period of expansion. Moreover, if other factors (credit market imperfections, higher exposure of start-ups, burdensome labor market regulations) are relevant, the difference in productivity levels between declining and non-declining firms may even increase during a crisis (Arrighetti et al., 2021; Carreira et al., 2022).

2.4 HD events and the role of idiosyncratic shocks

Episodes of firm decline tend to occur rapidly (mostly within a year) and are largely idiosyncratic (Carlsson et al., 2021). Firms operating in the same sector shrink and grow (in terms of the number of employees) side by side. The extant literature points out that productivity is the key driver of firm dynamics. On one hand, productivity *levels*, which reflect idiosyncratic characteristics such as routines and management practices, certainly determine firm performance (Esteve-Pérez et al., 2018), and we expect the probability of a firm experiencing an HD event to be negatively associated with them. On the other hand, *changes* in productivity, linked to research and development (R&D) and innovation, investments in human and physical capital (Battisti et al., 2019; Bartoloni et al., 2021), may also reduce a firm's likelihood of experiencing an HD event. Besides, the likelihood of experiencing an HD event may well depend on differential access to external finance, from which heterogeneous firms may benefit. In addition to supply-side factors, idiosyncratic shifts in demand may be relevant too. We expect HD events to be less frequent in markets with growing demand than those with shrinking demand. Moreover, HD events should be less common when the firm's market share is expanding than when it is decreasing.

It is fundamental to assess the relative role of demand-side and supply-side drivers because even if sudden firm-level employment contractions in "normal times" are likely related to idiosyncratic demand shocks, drastic employment downsizing may also arise from poor productive and financial performance (Denis and Shome, 2005). In this respect, we further contribute to the literature on the distinct impact of firm-level supply and demand shocks on firm outcomes (Pozzi and Schivardi, 2016; Carlsson et al., 2021), which has so far focused on the role of these shocks for firm closure, firm growth, and labor adjustment. By spotting firm-year-specific HD events, we consider that the bulk of large firm-level adjustments mostly take place within a year, and it is largely idiosyncratic. Moreover, the multi-scope nature of the survey used in this paper allows us to assess the relative role of a large group of supply- and demand-side factors that could affect the likelihood of facing an HD event.

2.5 The growth paths in the aftermath of an HD event

Firms that experience an HD event may or may not exit the market in its aftermath. Therefore, it is important to identify the drivers that help a firm return to a sustainable growth path (or even attain high growth) and avoid failure after an HD event. A growing body of literature has recently focused on the characteristics that make some firms more resilient (i.e., they can return to their pre-existing condition or adapt) than others in terms of higher survival chances. For example, Battisti et al. (2019) assessed the positive role that learning mechanisms played in firm resilience in a sample of 245 small businesses in New Zealand, which survived during the period from 2007–2011. Similarly, Landini et al. (2020) showed that firms that were more intensive in intangible assets (i.e., research expenditures, patents, licenses, and trademarks) were characterized by higher survival chances in the period from 2007–2014.

Although these studies provide insights into firm resilience, they group all alternatives that a firm could embrace after an external negative shock into two categories: market exit or survival. In Section 4.2, we explore firms' growth paths after experiencing an HD event by considering three alternative growth trajectories—*fast growth*, *moderate either positive or negative growth,* and *exit from the market*, thus adopting a more comprehensive set of "fates" that a firm may undergo after that event. To our knowledge, no previous work has investigated this set of multiple alternative growth trajectories that a firm may take in the face of a high and sudden decline, as well as the determinants of these trajectories.[6] In this respect, we contribute to the emerging literature on firm growth

[6] Only a few studies have examined the relationship between downsizing and bankruptcy (Powell and Yawson, 2012; Zorn et al., 2017).

paths, which seeks regularities in the medium- and long-term growth trajectories of firms. Previous studies have mainly analyzed the performance of firms in "normal times". However, there is a need to understand whether and how firm growth trajectories in "normal times" differ—in their likelihood and determinants—from those in "bad times". To this end, in Section 4.4, we compare the growth trajectories and their drivers for those firms that have experienced an HD event with those of their counterparts that did not experience an HD event.

3 Data, empirical approach, and descriptive analysis

3.1 Data

We use firm-level data extracted from the *Encuesta Sobre Estrategias Empresariales* (ESEE) over the period 2001–2016. The ESEE is a non-mandatory annual survey sponsored by the Spanish Ministry of Industry and conducted by the SEPI Foundation. The design of the survey excludes firms with fewer than 10 employees.[7] Manufacturing firms with 10 to 200 employees were randomly sampled using two-digit industries (NACE rev. 2) and size, and all firms with more than 200 employees were invited to participate. The survey annually incorporates new firms based on the same sampling criteria, so the sample is representative of the Spanish manufacturing sector over time. All manufacturing industries are included in the ESEE, except coke manufacturers and refined petroleum activities (i.e., division 19).[8] Our initial sample consists of an unbalanced panel including about 2,000 manufacturing firms per year in the period from 2001–2016.

This dataset has three features that suit our purpose in this study. First, its long time span allows us to observe many firms that experience HD events, and, on some occasions, several HD events have occurred to the same firm over its life cycle. Second, the dataset embraces different phases of the business cycle in Spain. Third, the multi-scope nature of this survey allows us to consider a rich set of factors associated with both HD events and post-HD firm trajectories.

3.2 Definition of HD, empirical approach, and explanatory variables

In line with previous studies (Whetten, 1987; Wiseman and Bromiley, 1996), we use a proxy of the negative evolution of firm size to measure high decline. First, firm i's growth rate from $t\text{-}1$ to t is defined as the one-year log difference in firm i's size, $gr_{it} = \ln(SIZE_{it}) - \ln(SIZE_{it-1})$. $SIZE_{it}$ is equal to the sum of full-time permanent workers, 50% of part-time permanent workers (both measured on 31 December), and the quarterly average number of non-permanent employees throughout the year. Second, we employ a relative definition of HD. Firm i is defined as suffering an HD event in year t ($HD_{it} = 1$) if gr_{it} lies in the lowest decile of the distribution of one-year employment growth rates of the firms in the same industry in the sample in the period from 2001–2016.[9] To account for differences between industries, but avoiding a too narrow definition that reduces the number of firms in the reference set, we distinguish between eight major manufacturing sectors.[10] Episodes of abrupt firm size reduction in terms of employment may not necessarily go hand in hand with similar reductions in sales or

[7] This threshold is commonly used in many surveys, such as the EU-EFIGE/Bruegel-Unicredit database (administered in 2008–2009 by the Directorate General Research of the European Commission through its Seventh Framework Programme), which gathers data on a representative sample of European manufacturing firms with more than 10 employees.

[8] This also was not a methodological decision, but it was based on the survey design. However, the number of firms in these industries constitute a tiny fraction of the total number of manufacturing firms. According to the Spanish Central Business Register, in 2015, firms in these industries represented 0.027% of the total number of manufacturing firms with more than 10 employees.

[9] An alternative approach would be to use the decile of the individual years analyzed as a reference. However, in that case we would have the same percentage of HD events (10%) in each year and the temporal comparison would be less informative since we are also interested in the relationship between HD events and the business cycle.

[10] The ESEE provides disaggregated information for 20 manufacturing industries. For the definition of industry-based HD events, we aggregated them into the following 8 sectors: Food, beverages and tobacco; Textiles, wearing apparel, leather and footwear; Wood, paper and printing; Chemicals, pharmaceutical products, rubber and plastics; Mineral products and metals; Machinery, computers, electrical and electronic equipment; Motor vehicles and other transport equipment; Furniture and other manufacturing.

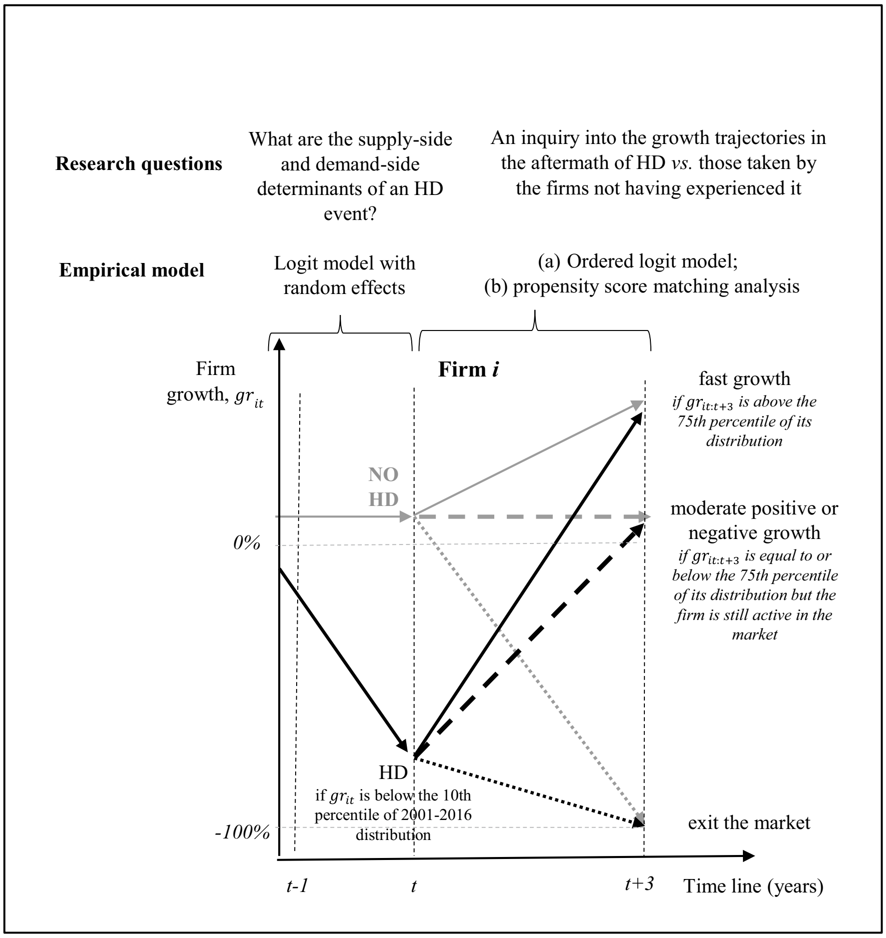

Fig. 1 Timeline representation of the HD events and subsequent growth trajectories

profits. Thus, we are clearly emphasizing one aspect of firms' decline (i.e., the reduction of employment) and leaving aside other firm outcomes that are first-order concerns for both managers and entrepreneurs. However, from a policy standpoint, focusing on employment reduction gives us the possibility of furnishing through our work some implications for aggregate employment stability and growth.

Building on the definition of HD, the Figure 1 sketches out the reference model that provides guidance for the empirical analysis.

Our empirical approach follows a procedure in two steps. First, we investigate the drivers of the HD events in year *t* using a random effects logit model and relying on a large vector of supply-side and demand-side factors observed in year *t-1*. This analysis helps unravel the factors that precipitated the firms' sudden decline (i.e., HD event, thick black line in Figure 1) or not (thin grey line).

Second, we assess both the likelihood of occurrence and the drivers of the three growth trajectories between year *t* and *t+3* —*fast growth*, *moderate positive or negative growth,* and *exit from the market*— in the aftermath of an HD event. We use an ordered logit model, which is complemented by a propensity score matched (PSM) sample analysis, to compare the three trajectories in a group of firms that have experienced an HD event (black lines) with the trajectories of firms that have not experienced such an event (grey lines).

Decline events may be due to factors that are beyond a firm's control (i.e., a recession or a specific

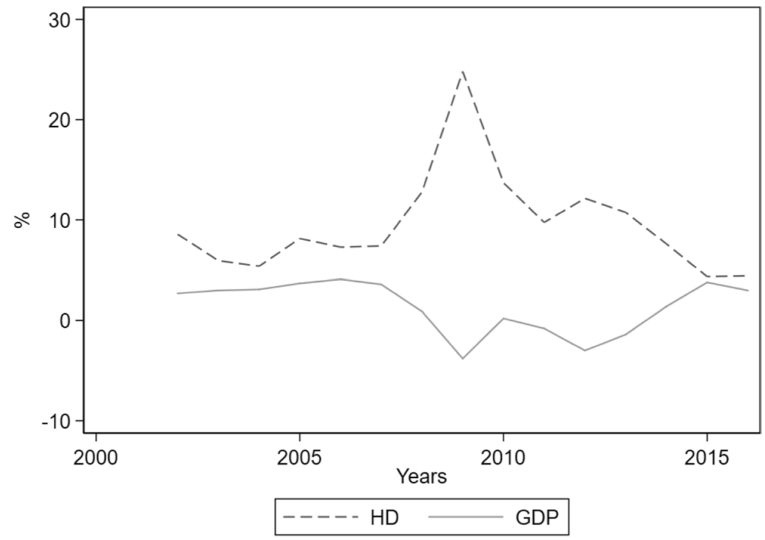

Fig. 2 HD events (percentage of firms in each year) and GDP growth rates (2002-2016)

shock in the demand it faces), but their occurrence may be lessened (or enhanced) by a firm's characteristics and strategic choices. To facilitate the interpretation of the results of the empirical analysis, we group the determinants of HD into five categories: (i) supply-side determinants: the labor productivity *level*, the introduction of product and process innovations, and investments in human and physical capital (as proxies for labor productivity *changes*); (ii) demand-side determinants: the stance of the market in which a firm is active and the evolution of the firm's market share; (iii) the firm's financial structure; (iv) an indicator variable, *HG*, which identifies whether a firm experienced a high-growth event in year *t-1* in comparison to other firms in the industry; (v) other strategic choices undertaken by a firm (e.g., changes in the firm's charged prices and product diversification); (vi) variables capturing the structural characteristics of the firm (i.e., age, size, and ownership type). Table A.1 in the Online Appendix provides variable definitions and summary statistics.

3.3 The distribution of HD events over the business cycle and the role of demand

Figure 2 shows the percentage of firms experiencing an HD event in each year and the annual GDP growth rate of the Spanish economy over the sample period.

At first glance and in line with our expectations, a clear countercyclical pattern in the occurrence of HD events emerges. More HD events occurred in years with a more severe macroeconomic downturn, specifically from 2008–2013.[11] Episodes of rapid and significant contraction in the number of employees, as mechanisms of reallocation of labor across firms, are more frequent in periods of economic contraction than in expansionary periods. To grasp an idea of the relationship between productivity and HD in the downturn and upturn of the business cycle, Table 1 shows the median values of labor productivity for firms that have experienced an HD event and for those that have not, both in the period

Table 1 Median labor productivity of firms experiencing an HD event and those that do not

	HD=0	HD=1
Upturn	102.60	79.91
Downturn	100.15	68.39

Upturn refers to 2001-2007 and 2014-2016 periods; downturn refers to 2008-2013 period. Labor productivity is defined as total real sales (thousands of €) per employee

[11] This result is confirmed when it is controlled for industry-specific unobservable characteristics in a regression analysis. Table A.2 in the Online Appendix shows the results of a random effects logit regression in which the probability of an HD event is the function of a vector of industry (2-digit level, NACE Rev. 2) and year dummies. The omitted/baseline year is 2001, which the coefficients of the other years are compared to. As can be seen, the years 2008, 2009, 2010, 2012, 2013 show the highest probabilities of the occurrence of an HD event.

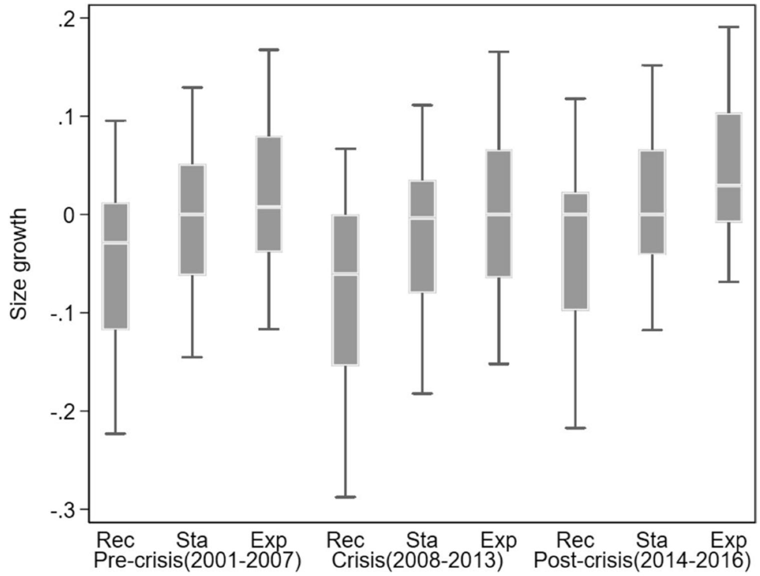

Fig. 3 Box plots of the distribution of employment growth according to the business cycle and the firm's market (demand) dynamics. Note: The boxes show the 25th, median, and 75th percentile of size (employment) growth. The adjacent lines show the 90th (upper) and the 10th percentile (lower) of size growth. Size growth is calculated for subsamples of firms (of all industries) that define their markets as recessive (Rec), stable (Sta), and expansive (Exp) in each time period

2008-2013 (Great Recession for Spain) and in the period 2001-2007 together with the period 2014-2016 ("normal times").

In both sub-periods, firms facing an HD event show a lower median labor productivity than their counterparts that have not faced such a heavy contraction in terms of the number of employees. Therefore, (relatively) more jobs are destroyed in those firms that are less productive and this positively contributes to a better allocation of resources. Nonetheless, it is interesting to see that while the median labor productivity of firms not facing an HD event just slightly swings when comparing the upturn with the downturn, firms facing an HD event show a much lower median productivity during the recession than in "normal times". Consequently, the difference in median productivity levels between declining and non-declining firms has increased during the recession. We might take this result as a suggestion of the weakening of the cleansing effect during the 2008-2013 crisis for Spanish manufacturing firms. Indeed, the cleansing hypothesis would imply that the productivity threshold associated with surviving in the market should be higher and, therefore, all surviving firms should be more productive. This result is consistent with the findings of Foster et al. (2016). In the case of Spain, credit market imperfections and the regulation of the dual labor market may have played a role in lessening the effectiveness of the cleansing effect of recessions in terms of an accelerated productivity-enhancing reallocation of resources.[12]

Nevertheless, it is noteworthy that the markets in which firms operate have been affected differently by the Great Recession, leaving micro-level heterogeneity (in terms of firms' prospects for growth and decline) on the demand side to be explored further. In Figure 3, relying on a battery of box plots, we show the main percentiles of the distribution of employment growth rates according to the economic cycle and each firm's market dynamics. The variable *MARKETDYN*, which is a proxy for the dynamics of the market demand a firm faces (see Table A.1 for definitions), includes three categories: recessive (R), stable (S), and expansive (E).

HD events always correspond to (high) negative growth rates, independently of the period being considered: indeed, the bottom 10% of the employment growth rate distribution, shown as a low adjacent value of the box plot, was clearly below zero in all periods. Regardless of the dynamics of the demand a firm faces in its main market, the entire box plot shifted downward, and the lower adjacent value

[12] Bentolila et al. (2019) provide a detailed overview on the effects of dual labour markets (i.e., employment protection legislation that induces two-tier segmentation of labour markets) and how they hamper the reallocation of workers from lower to higher productivity jobs during recessions. They refer to Spain as a "*a bellwether country regarding duality*".

(bottom 10%) was far lower during the contractionary period than before and after it. However, within both expansionary (2001–2007 and 2014–2016) and contractionary (2008–2013) periods of the business cycle, firms active in expansive markets (where demand increased) grew more than firms active in stable or recessive markets. HD events are less frequent in a market in which demand is growing with respect to a market with shrinking demand. Moreover, sudden firm-level employment contractions in "normal times" are related to demand shocks.

4 Econometric analysis

4.1 The determinants of an HD event

In the first part of the empirical analysis, we examine the drivers of HD. This provides insights into the supply-side and demand-side factors that affect a firm's likelihood of experiencing an HD event.

To examine the probability that a firm experiences an HD event and its determinants, we estimate a logit model with random effects:

$$P\left(HD_{it} = 1|\mathbf{X}_{it-1}\right) = P\left(\boldsymbol{\beta}'\mathbf{X}_{it-1} + \alpha_i\right) \tag{1}$$

where $P = \{1 + \exp(-z)\}^{-1}$ is the logistic function, α_i, which is i.i.d. with $N\left(0, \sigma_v^2\right)$, is a random component that is included to capture the (unobserved, time-invariant) heterogeneity across firms; and $\mathbf{X}_{it-1}$ is the vector of variables that proxy the factors associated with an HD event. In all estimates, the explanatory variables $\mathbf{X}_{it-1}$, are introduced as one-year lagged to mitigate simultaneity issues. When a variable enters the model as categorical, *N-1* categories are included, and the coefficients are interpreted as differences with respect to the omitted/baseline category. A vector of year fixed effects is included to control for macroeconomic dynamics (i.e., business cycle) that, as discussed in the previous sections, are relevant in explaining HD patterns over time. A vector of twenty (2-digit level, NACE Rev. 2) industry dummies is added to control for industry-specific time-invariant differences in the occurrence of HD events. Given that HD (and HG) is defined by comparing the firm growth rate in year *t* with the sectoral distribution of firm growth rates across eight aggregate manufacturing sectors, the vector of twenty industry dummies should control for a finer level of unobserved heterogeneity across sectors. All estimations include cluster-robust standard errors at the firm level to account for within-cluster correlation.

Table 2 displays the estimates of different specifications of the random effects logit model (1). Col. 1 shows the results for the entire sample, while col. 2 and col. 3 present the results of the sub-samples of SMEs and large enterprises (LEs), which are defined as firms with 200 or fewer employees and firms with more than 200 employees, respectively. In col. 4 and col. 5, we further explore the role of the different phases of the business cycle in explaining the likelihood of the occurrence of an HD. Some interesting results stand out. First, we find that firms with higher levels of productivity show a lower probability of experiencing an HD event, which is predicted in both the industrial dynamics literature (Jovanovic, 1982; Silverberg et al. 1988; Hopenhayn, 1992; Dosi et al., 1995) and the organizational decline literature (Whetten, 1987). The relationship is stronger in the sub-sample of SMEs. Second, regarding our proxies for productivity change, the introduction of a new product in year *t-1* (*PROD_INN*) does not significantly reduce the probability of experiencing an HD event in year *t*. This unexpected result indicates the complex relationship between the introduction of new products and firm dynamics (Goedhuys and Veugelers, 2012). By contrast, process innovation (*PROC_INN*) is an effective tool in reducing the conditional probability of facing an HD event for SMEs. Additionally, a firm's investment in physical (*PHYSICAL_CAP*) and human (*HUMAN_CAP*) capital in year *t-1* reduces the likelihood of experiencing an HD event in year *t*, but both their impact is less precisely estimated in the sub-sample of large firms. Overall, supply-side determinants are effective tools for lowering the probability of facing abrupt decline for SMEs. LEs' likelihood of experiencing an HD event seems to be less related to these factors.

Third, in line with Fig. 3, our estimates indicate that a firm that operates in a market with a stable or expansive demand ($MARKETDYN_S$ and $MARKETDYN_E$, respectively), is less likely to suffer an HD event compared with firms in recessive markets ($MARKETDYN_R$, the omitted category). A stable or expansive firm's market share ($MARKETSH_S$ and $MARKETSH_E$) is also associated with a lower probability of an HD event compared with a shrinking market share

Table 2 Random effects logit model: What factors do determine an HD event?

	(1)	(2)	(3)	(4)	(5)
				The role of the business cycle	
	All firms	SMEs	LEs	Upturn	Downturn (differential effect)
PRODUCTIVITY	-0.0015*	-0.0030***	-0.0002	-0.0014**	-0.0000
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
PROD_INN	-0.0791	-0.0929	-0.1375	-0.0226	-0.0773
	(0.087)	(0.102)	(0.182)	(0.127)	(0.165)
PROC_INN	-0.2618***	-0.3450***	0.0411	-0.2734**	0.0439
	(0.071)	(0.081)	(0.171)	(0.110)	(0.140)
HUMAN_CAP	-0.2195***	-0.2888***	-0.0379	-0.2458**	-0.0449
	(0.068)	(0.077)	(0.203)	(0.103)	(0.129)
PHYSICAL_CAP	-0.4122***	-0.4635***	-0.2247	-0.3725***	0.0692
	(0.069)	(0.071)	(0.387)	(0.101)	(0.131)
$MARKETDYN_S$	-0.4743***	-0.4201***	-0.6900***	-0.4239***	-0.0459
	(0.073)	(0.082)	(0.186)	(0.122)	(0.149)
$MARKETDYN_E$	-0.6730***	-0.6511***	-0.6698***	-0.5916***	-0.0425
	(0.112)	(0.128)	(0.247)	(0.169)	(0.217)
$MARKETSH_S$	-0.3136***	-0.3273***	-0.3053	-0.2629**	-0.0567
	(0.073)	(0.080)	(0.188)	(0.127)	(0.152)
$MARKETSH_E$	-0.5083***	-0.5606***	-0.2956	-0.5345***	0.0942
	(0.109)	(0.122)	(0.263)	(0.171)	(0.221)
LEVERAGE	0.7572***	0.7361***	0.4799	0.4672**	0.4406*
	(0.130)	(0.141)	(0.395)	(0.201)	(0.238)
HG	0.2131**	0.2205**	0.0816	0.2198*	-0.0805
	(0.090)	(0.097)	(0.255)	(0.120)	(0.182)
PRICEVAR	-0.0154**	-0.0149*	-0.0136	-0.0135	0.0179
	(0.008)	(0.009)	(0.019)	(0.014)	(0.016)
DIVERSI	0.1322	0.0454	0.1932	0.0945	0.0481
	(0.087)	(0.094)	(0.213)	(0.130)	(0.154)
AGE	-0.0044**	-0.0065***	0.0005	-0.0061***	0.0010
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
SIZE	-0.0163**	0.6300***	-0.0104*	-0.0278**	0.0212
	(0.007)	(0.073)	(0.006)	(0.013)	(0.015)
FAMILY	-0.1333**	-0.0813	-0.3749	-0.0061***	-0.1979*
	(0.068)	(0.074)	(0.254)	(0.002)	(0.105)
DOWNTURN *(08-13)*				0.7806***	
				(0.073)	
Constant	-1.8923***	-1.7595***	-3.7531***	-1.6814***	
	(0.258)	(0.266)	(0.761)	(0.212)	
Ln of variance of the firm random effects	-0.5131***	-0.4978***	-0.0338	-0.4935***	
	(0.139)	(0.159)	(0.335)	(0.138)	
Industry FEs (2-digit NACE rev.2)	Yes	Yes	Yes	No†	
Year FEs	Yes	Yes	Yes	Yes	
Observations	19,896	14,869	4,961	19,896	

Firm-level clustered 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.†Year fixed effects are not included to estimate the coefficient δ of the *DOWNTURN* dummy

($MARKETSH_R$, the omitted category). Because in the empirical model we control for both productivity and technological characteristics, a variable accounting for the evolution of a firm's market share may be a good proxy for the idiosyncratic demand faced by the firm.

Fourth, firms with higher debt (*LEVERAGE*, i.e., the ratio of total debts to total debts plus shareholders' equity) endure a higher probability of experiencing an HD event, which is in line with Hambrick and D'Aveni (1988) and Wiseman and Bromiley (1996). Firms that experienced a rapid expansion in *t-1* (*HG* = 1 if the firm's employment growth rate in *t-1* was in the top 10% of the distribution of industrial growth rates) are more likely to experience a heavy contraction in year *t* than their counterparts are. This result supports the "success breeds failure" phenomenon (Pierce and Aguinis, 2013; Coad et al. 2020), and is also compatible with deliberate downsizing made by successful profit-maximizing firms that focus on their core competences or internal reorganization after high growth.[13]

Fifth, the coefficients of the other "traditional" strategic variables are also noteworthy. On one hand, firms that are active in markets in which product prices increase (*PRICEVAR*) show a lower probability of HD in year *t,* which may be capturing the specific market power of these firms. On the other hand, diversification (*DIVERSI*) is positively but not significantly associated with a higher probability of facing an HD event. Related to the latter, it should be noted that it measures whether the firm has diversified production in at least one sector other than the main sector, defined at 3-digits NACE rev.2. However, we do not have precise information on the nature and timing of the diversification process undertaken by firms. In particular, Kim et al. (2016) obtain an inverted U-shaped relationship between technological diversification and firm growth.

Sixth, as for the structural characteristics of the firm, we find a negative relationship between firm age (*AGE*) and the likelihood of experiencing an HD event in year *t*. In the sub-sample of LEs, the relationship is positive but much smaller in magnitude and not statistically significant. The probability of experiencing an HD decreases according to firm size (*SIZE*) in the overall sample (col. 1). However, in the sub-sample of SMEs, the likelihood of experiencing an HD event increases according to firm size, while it decreases in the sub-sample of LEs.[14] Family-owned firms (*FAMILY*) are less likely to face an HD event, a result that is in line with the obtained by Stavrou et al. (2007). These firms may have benefitted from fewer conflicts of interest between managers and shareholders, which may have led to more stable growth behavior.

Overall, the coefficients of the determinants of an HD episode are rather consistent in the sub-samples of SMEs and LEs (col. 2 and col. 3 of Table 2, respectively). However, coefficients are less precisely estimated in the case of LEs, because their sub-sample is smaller than that of SMEs and because the majority of HD events occur in the SMEs category.[15] Indeed, while 11,5% of SMEs in the study sample show HD events, this percentage is 5% in the LE category.[16]

The results indicate that, once we control for annual macroeconomic shocks and industry unobserved time-invariant characteristics, both supply-side and demand-side factors play a role in explaining the likelihood that a firm experiences an HD event. Moreover, the financial structure of the firm and some structural characteristics are also relevant to explain the probability of an HD event.

To examine the role of the different phases of the business cycle in explaining HD and its determinants, we add to Eq. (1) an interaction effect between the determinants of HD and a dummy variable equal to one in the period 2008-2013. Then, we estimate the following random effects logit model:

$$\begin{aligned} &P\left(HD_{it} = 1|\mathbf{X}_{it-1}\right) \\ &= P\left(\beta'\mathbf{X}_{it-1} + \delta DOWNTURN + \gamma'\mathbf{X}_{it-1} \bullet DOWNTURN + \alpha_i\right) \end{aligned} \tag{2}$$

[13] We thank two reviewers for pointing out these possibilities. We cross-refer the reader to Section 5.2 for an in-depth analysis of the growth performance of the firm before facing an HD event.

[14] We cross-refer the reader to Section 5.1 for a focus on the role of firm age and firm size in abrupt decline.

[15] Hambrick and D'Aveni (1988: p. 1) suggest that the "The failure of large corporations, […] may require its own […] perspective […]", thus advocating the separate analysis of the decline phenomenon in LEs with respect to SMEs. Even if we share this qualitative judgement, we still prefer to include firms of all size classes in our analysis to better appreciate the role played by structural factors and to ensure that the analysis is as broad as possible.

[16] In Section 5.1 we show that these results are robust also when we split the sample according to below- and above-median size, and below- and above-median age.

$\widehat{\delta}$ provides an estimation of the difference in the likelihood of facing an HD event by contrasting the period of the downturn (2008-2013) with the period of the upturn (2001-2007 and 2014-2016); $\widehat{\gamma'}$ captures the differential effects of the determinants of an HD event in the downturn with respect to the upturn. Results are shown in Table 2 in two separate columns (cols. 4 and 5) for ease of comparison: estimates of $\beta\prime$ (effects of the determinants in the upturn) are reported in col. 4 and estimates of $\gamma\prime$ are reported in col. 5. The coefficient of the dummy *DOWNTURN*, δ, is reported at the bottom. $\widehat{\delta}$ is positive and significant, supporting our expectation that (even after controlling for supply-side, demand-side, financial, strategic, and structural characteristics of the firm and firm-level unobserved heterogeneity), the probability of experiencing an HD event is significantly higher during a crisis than in "normal times". Moreover, among all the determinants of HD, only two have a differential effect that is statistically significant during the downturn, i.e., family ownership and financial leverage. The former might be associated with factors such as family norms and values, for instance, building a family legacy and maintaining control of the firm could make dynastic managers more prone to avoid firm exit and HD at all costs (Bertrand and Schoar, 2006). This may enhance the incentives to invest resources in establishing long-lasting kinship networks to get access to public resources related to counter-cyclical measures adopted by the government to avoid massive layoffs. As for financial leverage, the result is coherent with the idea that, during a downturn, financial exposure plays an additional detrimental role in predicting abrupt decline events. Putting this result in perspective with the non-significant coefficient related to the level of labor productivity and the other supply-side determinants, we suggest that credit needs are more relevant than differences in productivity to explain the probability of HD during a crisis with respect to an upturn phase of the business cycle (Barlevy, 2003).

In the next section, we turn to examine three alternative growth trajectories that a firm may take in the aftermath of an HD event.

4.2 Growth trajectories in the aftermath of HD: Baseline results

This section focuses on the likelihood and determinants of three possible growth trajectories —*fast growth*, *moderate positive or negative growth,* and *exit from the market*-- that a firm may take in the aftermath of facing an HD event. Specifically, the aim is to determine the factors that may enhance or decrease the likelihood of undertaking each medium-run growth trajectory (from t to $t+3$), conditional on having experienced an HD event in year t.

To address this question, we use an ordered logit model. In this context, Y^* is the latent variable (i.e., the growth rate) across progressively higher thresholds:

$$Y^*_{it:t+3} = \boldsymbol{\beta}'\boldsymbol{X_{it}} + \varepsilon_{it:t+3} \tag{3}$$

Three categories that corresponded to alternative trajectories are defined by two thresholds (α_1 , α_2), such that if $Y^*_{it:t+3} \leq \alpha_1$, the trajectory is *exit from the market* (in the period from t to $t+3$). If $\alpha_1 < Y^*_{it:t+3} \leq \alpha_2$, the trajectory is *moderate either positive or negative growth* (the firm's growth rate is equal to or below the 75th percentile in the three-year growth rate distribution). Finally, if $Y^*_{it:t+3} > \alpha_2$, the trajectory is *fast growth* (above the 75th percentile of the three-year growth rate distribution). The probability of category j is defined as follows:

$$\begin{aligned} Pr\left(Y_{it:t+3} = j\right) &= \Pr\left(\alpha_{j-1} < Y^*_{it:t+3} \leq \alpha_j\right) \\ &= F\left(\alpha_j - \beta' X_{it}\right) - F\left(\alpha_{j-1} - \beta' X_{it}\right) \end{aligned} \tag{4}$$

where $\alpha_0 = -\infty$, $\alpha_3 = \infty$ and F is the logistically distributed function. All explanatory variables are measured at the beginning of the period (year t) to reduce simultaneity issues. In all estimates, industry and year fixed effects are included, and cluster-robust standard errors at the firm level are adopted to account for within-cluster correlation. Table 3 shows the estimates of the ordered logit model. Col. 1 refers to the entire sample, while col. 2 and col. 3 refer to the subsamples of SMEs and LEs, respectively.

After a firm experiences an HD event, some supply-side factors seem to play a relevant role as levers to tackle the decline and return to a trajectory of stability and growth. Interestingly, higher levels of productivity do not increase the likelihood of adopting *fast growth* with respect to the other two trajectories. However, a firm's investments in process innovation, human capital, and physical capital are associated with a higher likelihood of undergoing *fast growth*. This finding suggests that investments in both tangible and intangible assets are particularly important for achieving recovery

Table 3 Ordered logit model estimates: What happens in terms of medium-run growth trajectories, in the aftermath of an HD event?

	(1) All firms	(2) SMEs	(3) LEs
PRODUCTIVITY	0.000	0.000	0.000
	(0.000)	(0.001)	(0.000)
PROD_INN	-0.059	0.018	-0.142
	(0.156)	(0.185)	(0.533)
PROC_INN	0.376***	0.336**	0.756*
	(0.141)	(0.155)	(0.449)
HUMAN_CAP	0.362***	0.440***	0.613
	(0.130)	(0.137)	(0.552)
PHYSICAL_CAP	0.350**	0.387***	0.406
	(0.136)	(0.141)	(1.128)
$MARKETDYN_S$	0.141	0.162	0.101
	(0.152)	(0.168)	(0.503)
$MARKETDYN_E$	0.199	0.221	0.933
	(0.232)	(0.264)	(0.610)
$MARKETSH_S$	0.547***	0.517***	0.856
	(0.141)	(0.152)	(0.569)
$MARKETSH_E$	0.933***	0.911***	1.036
	(0.259)	(0.294)	(0.794)
LEVERAGE	-0.455*	-0.415	-0.723
	(0.273)	(0.288)	(1.091)
PRICEVAR	0.025**	0.022	0.039
	(0.013)	(0.013)	(0.056)
DIVERSI	0.033	0.141	-0.637
	(0.172)	(0.189)	(0.579)
AGE	-0.007**	-0.006	-0.015
	(0.003)	(0.004)	(0.010)
SIZE	-0.034**	-0.361***	-0.034
	(0.014)	(0.134)	(0.023)
FAMILY	0.279**	0.215	0.286
	(0.130)	(0.138)	(0.592)
Cons. *(1 vs 2&3)*	-1.831***	-1.793***	-2.109
	(0.438)	(0.490)	(1.622)
Cons. *(1&2 vs 3)*	1.296***	1.208**	3.684**
	(0.435)	(0.488)	(1.782)
Industry FEs (2-digit NACE rev.2)	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
Observations	1,482	1,285	197

Firm-level clustered 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

from an HD event (Wiseman and Bromiley, 1996). Moreover, if we consider the introduction of new processes and investment in physical and human capital as proxies for productivity change, these results are somewhat in line with Dosi et al. (2015), who find that productivity changes have a greater impact on firm growth than productivity levels in manufacturing firms in four developed economies.

Regarding demand-side factors, both a stable and an expansive dynamism of the main market in which a firm is active, and a stable or growing market share increase a firm's probability of enjoying *fast growth* with respect to the other two trajectories, but only the effect of the dynamics of the firm's market share is statistically significant. This result supports the view that idiosyncratic demand-side positive shocks may be more relevant than market shocks in re-taking a medium-run growth trajectory (from *t* to *t+3*), conditional on having experienced an HD event in year *t*. Strategies to increase a firm's idiosyncratic demand (e.g., rebuilding a broad and solid customer base and enhancing a firm's reputation) are essential in this respect.

We also find that high financial leverage negatively affects the likelihood of following a *fast growth* trajectory compared with the other two trajectories. In this respect, this result may suggest that if the HD event has not been an opportunity for the firm for deleveraging, it is hard to re-take a sustainable path of stability and growth. Charging higher prices is positively associated with taking a *fast growth* trajectory compared with the other two trajectories. Conversely, diversifying is not statistically associated with any particular growth path in the aftermath of an HD event.

As for the firm's structural characteristics, they are relevant in explaining the growth trajectory taken by the firm after facing an HD event. In particular, the coefficient associated with firm age suggests a negative relationship between age and *fast growth* after an HD event. Firm size is also negatively related to the likelihood of undertaking *fast growth* with respect to both *moderate positive or negative growth* and *exit from the market*, suggesting that even after suffering an HD event, smaller firms grow faster (Daunfeldt and Elert, 2013). Family ownership is associated with a higher likelihood of *fast growth* with respect to the other two trajectories when an HD event has occurred. For LEs (col. 3), the coefficients associated with most of the determinants are generally in line with those shown for SMEs (col. 2), but less precisely estimated, which might be due to the low number of observations and the lower incidence of HD events.

Overall, the results show that when a firm experiences an HD event, several supply-side factors play a relevant role in the likelihood of subsequent medium-run growth trajectories, which leaves managers and entrepreneurs room for manoeuvre. More specifically, process innovation and investment in new plants, machinery, equipment, and employees' skills may prompt a firm's recovery from HD. Besides, demand-side factors, in particular, a stable or growing firm's market share increases its likelihood of achieving a *fast growth* trajectory. Finally, young and small firms do not suffer a specific liability in terms of their likelihood of returning to a trajectory of stability and growth.

Section 4.3 further investigates the role of productivity levels, innovation, and investments (as proxies for productivity change), and shows that the role of productivity in both the probability of facing an HD event and the likelihood of undertaking a specific growth trajectory after an HD event is not sensitive to the use of an absolute measure or a relative (to the yearly sectoral average) measure of productivity.

4.3 On the role of productivity, innovation, and investments

The estimates in Tables 2 and 3 may raise two concerns. First, an absolute measure of productivity, such as the one we introduce in Equations (1) and (4), may mix up the role of idiosyncratic productivity shocks and industry-wide shocks. Second, one may argue that the considered supply-side determinants (the level of labor productivity, the introduction of new products and processes, and investments) are correlated.[17] In this section, we further explore these two issues, first by including labor productivity relative to the annual sectoral average in the empirical models, and second, by examining the separate effects of each of the supply-side determinants on both the probability of facing an HD event and the likelihood of taking a certain growth trajectory in the aftermath of that event. Results are shown in Table 4.

The top panel shows the random effects logit estimates, while the bottom panel shows the ordered logit estimates. Col. 1 in both panels shows the baseline results (Table 2, col. 1, and Table 3, col.1, respectively) for ease of comparison. In col. 2, we introduce labor productivity relative to the annual sectoral average.[18] In col. 3 we include a vector of sector-year fixed effects in the empirical models. The inclusion of these effects allows us to control for annual sectoral average shocks in both the dependent and independent variables, thus "cleaning" coefficients' estimates from time-variant sectoral differences. Reassuringly, the magnitude and significance of the coefficients referring to productivity levels, innovation and investments in R&D, physical and human capital do not change in cols. 2 and 3 with respect to col. 1. This result holds both when assessing the role of these supply-side factors in the probability of facing an HD event (top panel), and in the likelihood of following a particular growth path after an HD event (bottom panel). Thus, our specification is not sensitive to the use of either an absolute or a relative (to the annual sectoral average) productivity measure.

Furthermore, in both the random effects logit and ordered logit models, we have considered five supply-side explanatory variables that are likely correlated: labor productivity levels and four dummies indicating whether the company introduces product innovations, process innovations, or whether it makes investments in human and physical capital. It is well known that process innovations and investments in training and physical capital positively affect productivity levels (Syverson, 2011). To check if these drivers show separate and consistent effects in the probability of facing an HD event, and, subsequently, in the probability of taking one specific growth trajectory, we re-run the empirical models in Eq. (1) and (4) and add this set of covariates sequentially. The results are shown in cols. (4)-(9) of Table 4. The top panel shows the estimates of the random effects logit model. Interestingly, the proxy we use for the level of productivity shows a negative and consistent coefficient in all specifications in which it is included (col.1, col.4, col.5, and col.6), either alone or combined with indicators for innovations or investment. A firm's productivity level, once

[17] We thank one reviewer for raising both concerns. Note that product innovation and labour productivity may be correlated solely because the latter is a revenue-based measure.

[18] For consistency with the definition of HD and HG events, we consider eight main manufacturing sectors (see Section 3.2).

Table 4 Random effects logit (Model 1) and ordered logit (Model 2) estimates: More on productivity, innovation and investments

			Model 1: Determinants of an HD event						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PRODUCTIVITY	-0.0015*		-0.0015*	-0.0019**	-0.0018**	-0.0015*			
	(0.001)		(0.001)	(0.001)	(0.001)	(0.001)			
PRODUCTIVITY		-0.0015*							
(deviation from sector-year average)		(0.001)							
PROD_INN	-0.0791	-0.0789	-0.0929		-0.1326		-0.0737	-0.1355	
	(0.087)	(0.087)	(0.088)		(0.086)		(0.087)	(0.086)	
PROC_INN	-0.2618***	-0.2621***	-0.2704***		-0.3531***		-0.2725***	-0.3755***	
	(0.071)	(0.071)	(0.072)		(0.069)		(0.071)	(0.069)	
HUMAN_CAP	-0.2195***	-0.2202***	-0.2470***			-0.2617***	-0.2573***		-0.3007***
	(0.068)	(0.068)	(0.068)			(0.067)	(0.067)		(0.066)
PHYSICAL_CAP	-0.4122***	-0.4129***	-0.4177***			-0.4544***	-0.4422***		-0.4860***
	(0.069)	(0.069)	(0.071)			(0.068)	(0.067)		(0.066)
Other firm-level determinants	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs (2-digit NACE rev.2)	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Sector-Year FEs	No	No	Yes	No	No	No	No	No	No
Observations	19,896	19,896	19,387	19,909	19,909	19,896	19,896	19,909	19,896
			Model 2: Growth trajectories in the aftermath of an HD event						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PRODUCTIVITY	0.000		0.000	0.000	0.000	0.000			
	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)			
PRODUCTIVITY		0.000							
(deviation from sector-year average)		(0.000)							
PROD_INN	-0.059	-0.060	-0.029		0.017		-0.062	0.012	
	(0.156)	(0.157)	(0.183)		(0.157)		(0.156)	(0.157)	
PROC_INN	0.376***	0.377***	0.434***		0.480***		0.379***	0.488***	
	(0.141)	(0.141)	(0.158)		(0.140)		(0.140)	(0.139)	
HUMAN_CAP	0.362***	0.363***	0.440***			0.396***	0.366***		0.402***
	(0.130)	(0.130)	(0.144)			(0.131)	(0.129)		(0.130)
PHYSICAL_CAP	0.350**	0.351***	0.300**			0.392***	0.351***		0.393***
	(0.136)	(0.136)	(0.145)			(0.135)	(0.136)		(0.135)
Other firm-level determinants	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs (2-digit NACE rev.2)	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Sector-Year FEs	No	No	Yes	No	No	No	No	No	No
Observations	1,482	1,482	1,482	1,482	1,482	1,482	1,482	1,482	1,482

Firm-level clustered standard errors in brackets. Statistical significance at the 10%, 5%, and 1% level is indicated by *, ** and ***, respectively. Coefficients of the other firm-level determinants, year, and industry dummies are not reported to save space

controlled for innovation and investment in physical and human capital, may well capture the role of idiosyncratic features of the firm, such as operational routines, human resources, and managerial practices. Furthermore, the results in col.1, col.5, col.7, and col.8 on the top panel indicate that, while product innovation is never significantly associated with the probability of facing an HD event, the introduction of a new process consistently reduces the probability of an HD event in all specifications in which it is included. Besides, a firm's investments in both human and physical capital reduce the probability of an HD event either when the other supply-side determinants are introduced in the model (col. 1, col. 6, col. 7) or when they stand alone (col. 9). The bottom panel of Table 4 presents the estimates of the ordered logit model. The association between the level of productivity and the probability of taking a *fast growth* trajectory with respect to both *moderate positive or negative growth* and *exit from the market* is neither statistically nor economically significant. Moreover, as shown in col. 4, col. 5, and col. 6, this result does not depend on the consideration or not of the other supply-side factors. The role of carrying out process and product innovation and investing in human and physical capital remain very similar to that in col. 1 for explaining firms' fates after an HD event.

Overall, while idiosyncratic features of the firm, such as operational routines, human resources, and managerial practices (which may well be captured by the *level* of productivity), are relevant for lessening the probability of facing an HD event, *changes* in firm productivity proxied by the introduction of new processes and investment in physical and human capital are key to perform well in the aftermath of an HD event, when a firm has to re-take a path of stability and growth (Dosi et al., 2015).

Section 4.4 compares the growth trajectories taken by firms that have experienced an HD event in year *t* with those followed by firms that have not experienced an HD event.

4.4 Growth trajectories in the aftermath of HD: A counterfactual analysis

To assess whether an HD event is a challenge for a firm (Whetten, 1987), it would be optimal to observe the likelihood and determinants of the trajectories undergone by the same firm (i.e., those that experienced HD in year *t*) in the absence of such an event. Although a proper counterfactual is not observable, it is possible to check whether the group of firms that experienced an HD event followed different growth trajectories with respect to their counterparts that did not experience such an event.

Some interesting insights into this issue are provided by Fig. 4, which shows the share of firms following the three growth trajectories (between year *t* and year *t+3*) according to whether the firm experienced an HD event in year *t*.

Trajectories are not equally distributed across firms. In particular, the probability of *exit from the market* between *t* and *t+3* (panel A) is much higher for firms that experienced an HD event in *t* (continuous line) compared with those that did not suffer an HD (dashed line). Similarly, firms that experienced an HD event in year *t* show a lower probability of both *moderate positive or negative growth* (panel B) and *fast growth* (panel C) compared with their counterparts. There are differences in the percentage of firms with a *fast growth* trajectory during the worst years of the business cycle, while these percentages are similar during the expansionary period. Table A.3 in the Online Appendix shows the distribution of the three trajectories in the overall period. As expected, we reject the null hypothesis of the equal distribution of the three trajectories between the two groups of firms.

This finding calls for an analysis of the relevance of the drivers of the three trajectories in the two groups of firms. Thus, we enrich Eq. (3) by including a dummy variable equal to 1 for firms that experience an HD occurrence in year *t*, HD_i, in addition to a full vector of interactions with X_{it}. The ordered logit model takes the following form:

$$Y^*_{it:t+3} = \boldsymbol{\beta}'\boldsymbol{X_{it}} + \delta HD_{it} + \boldsymbol{\gamma\prime X_{it}} \bullet HD_{it} + \varepsilon_{it:t+3} \qquad (5)$$

where the coefficients $\boldsymbol{\gamma}$ refer to the interaction terms. As described in the previous section, all explanatory variables are measured at the beginning of the period (year *t*) to reduce simultaneity issues.

The first two columns in Table 5 show the results of the ordered logit model.[19] Specifically, the second column shows the vector of coefficients $\boldsymbol{\gamma}$, which captures the differential effect of an explanatory variable x_{it} on the medium-run growth trajectories of firms that have experienced an HD event with respect to their counterparts.

[19] The analysis is conducted on the entire sample for the following reasons: (i) most HD determinants have a similar effect in the sub-samples of both SMEs and LEs (Table 2); (ii) the coefficients associated with several determinants of the growth trajectories are less precisely estimated in the sub-sample of LEs (Table 3).

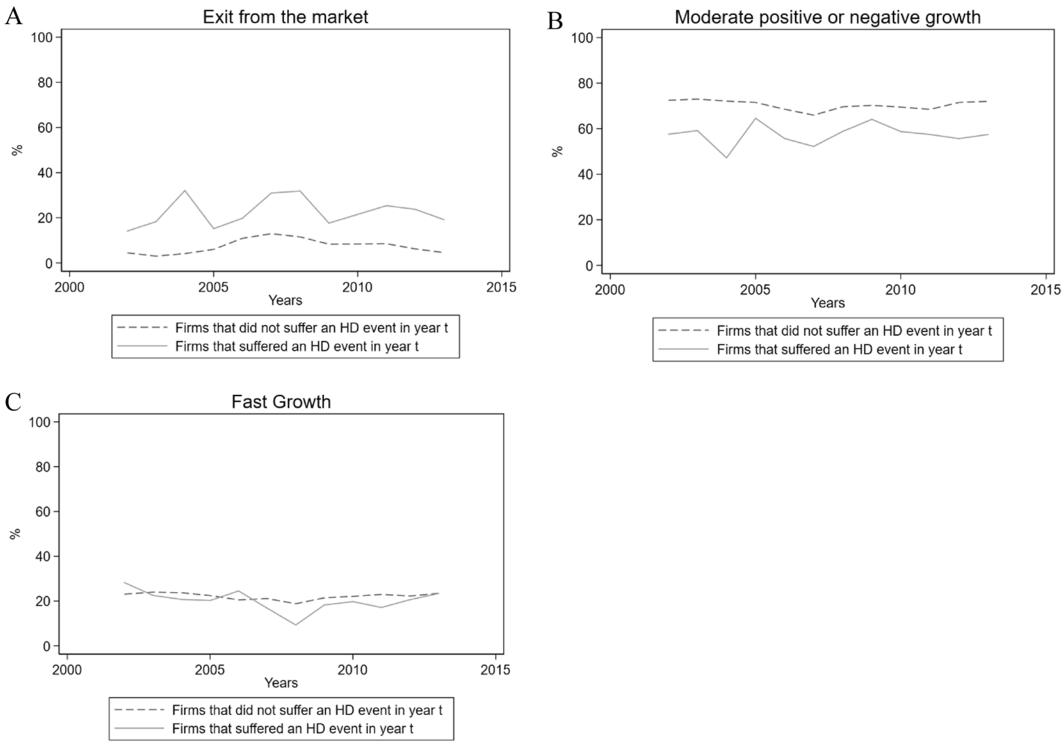

Fig. 4 Growth trajectories in the aftermath of an HD event

Even when a large vector of firm and market characteristics is controlled for, the coefficient of the HD_{it} dummy, δ, is negative and statistically significant, which is consistent with the patterns shown in Figure 4.

After finding that HD constitutes a burden in subsequent growth trajectories, it is noteworthy that the majority of the variables included in the analysis play a similar role in long-term growth in the two groups of firms (i.e., most coefficients $\boldsymbol{\gamma}$ are not statistically significant). More specifically, this finding applies to firm age and ownership type (structural characteristics), and market dynamics (demand-side factor). Moreover, this result is confirmed for most of the supply-side factors, such as investments in physical capital, the introduction of product and process innovation, and productivity. Financial leverage, diversification, and change in charged prices also do not exert different roles between the two groups of firms. Overall, while it is challenging for a firm that experiences an HD event to regain a path of stability or growth, the "recipe" for attaining that pattern is similar across firms regardless of whether they have experienced an HD event or not.

Nonetheless, some interesting differences emerge. First, regarding structural factors, the negative relationship between size and the likelihood of *fast growth* is stronger in the group of firms that experienced an HD event. Smaller firms, which were found to be more at risk of facing an HD event (Table 2), enjoy an advantage in the process of recovery in the aftermath of such an event. Second, regarding strategic factors, the positive effects of investments in human capital on the likelihood of *fast growth* (with respect to the other trajectories) are significantly stronger among firms that have undergone an HD event in *t*. Hence, improving the skills of employees is found to be a successful strategy for returning to a positive growth trajectory, especially after an HD event. Third, the dynamics of the firm's market share (demand-side factor) do matter in a more relevant way to regain a path of stability or growth if the firm has experienced an HD episode. This finding suggests that strategies for enhancing a firm's demand (e.g., re-establishing a wide and solid customer base and enhancing a firm's reputation) are essential.

Table 5 Ordered logit model estimates: Comparing post-HD episode growth trajectories for firms having experienced an HD event in *t vs.* the other firms

	Ordered logit model estimates: un-matched sample		Ordered logit model estimates: propensity score matched sample	
	(1)	(2)	(3)	(4)
	Coefficients β, referring to firms with HD=0 in year t	Coefficients γ of the interactions HD $\bullet X_i$, referring to the firms with HD=1 in year t	Coefficients β, referring to firms with HD=0 in year t	Coefficients γ of the interactions HD $\bullet X_i$, referring to the firms with HD=1 in year t
HD=1 in year t		-0.687***		-0.374
		(0.224)		(0.279)
PRODUCTIVITY	0.001***	-0.000	0.002***	-0.002***
	(0.000)	(0.000)	(0.001)	(0.001)
PROD_INN	0.061	-0.302	0.111	-0.344
	(0.058)	(0.206)	(0.153)	(0.232)
PROC_INN	0.263***	0.282	0.093	0.451**
	(0.050)	(0.183)	(0.131)	(0.213)
HUMAN_CAP	0.011	0.398**	0.242*	0.173
	(0.055)	(0.173)	(0.131)	(0.202)
PHYSICAL_CAP	0.369***	0.080	0.416***	-0.105
	(0.068)	(0.184)	(0.141)	(0.211)
MARKETDYN$_S$	0.351***	-0.100	0.314**	-0.090
	(0.057)	(0.205)	(0.132)	(0.224)
MARKETDYN$_E$	0.511***	-0.271	0.748***	-0.519
	(0.078)	(0.321)	(0.213)	(0.364)
MARKETSH$_S$	0.297***	0.456**	0.232*	0.421*
	(0.061)	(0.201)	(0.141)	(0.220)
MARKETSH$_E$	0.472***	0.804**	0.142	0.775**
	(0.082)	(0.346)	(0.222)	(0.394)
LEVERAGE	-0.340***	-0.107	-0.422	0.055
	(0.127)	(0.350)	(0.267)	(0.404)
PRICEVAR	0.013**	0.010	0.002	0.008
	(0.005)	(0.016)	(0.014)	(0.020)
DIVERSI	-0.111	0.143	-0.002	-0.013
	(0.072)	(0.226)	(0.167)	(0.252)
AGE	-0.005***	-0.003	-0.010***	0.003
	(0.001)	(0.004)	(0.003)	(0.004)
SIZE	-0.004	-0.031*	0.007	-0.032
	(0.003)	(0.018)	(0.012)	(0.020)
FAMILY	0.224***	0.083	0.266**	-0.055
	(0.057)	(0.170)	(0.123)	(0.190)
Cons. *(1 vs 2&3)*	-2.178***		-1.357***	
	(0.197)		(0.210)	
Cons. *(1&2 vs 3)*	1.804***		2.070***	
	(0.195)		(0.212)	
Industry FEs (2-digit NACE rev.2)	Yes		Yes	
Year FEs	Yes		Yes	
Observations	15,811		2,570	

Firm-level clustered 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

The results shown in the first two columns of Table 5 may be skewed by a selection bias. Indeed, HD events may not be randomly assigned across firms, as shown in Table 2. To reduce this endogeneity issue, we implement a PSM sample estimation (Rosenbaum and Rubin, 1983). This procedure aims to identify a control sample of firms that did not experience an HD event in year *t,* but whose observable characteristics are similar to those of firms that did experience such an event. Consequently, we reduce the concerns related to the non-random selection. We begin by calculating the probability that a firm experiences an HD event. Accordingly, we use the predictions from the random effects logit model shown in Table 2 (col. 1). These predictions are implemented in one-to-one nearest neighbor matching with replacement to obtain a sample of untreated firms (i.e., not experiencing an HD event in year *t*) that are similar to the treated ones (i.e., HD in year *t*) in all observable characteristics.[20] Following the usual approach to evaluate matching quality, Table A.4 in the Online Appendix shows the differences between the two groups in the means of the main covariates used to build the matched sample. As shown in Table A.4, the PSM reduces the differences between treated and untreated samples according to each variable.

After identifying the sample, we group the matched observations and perform two main analyses. First, we analyze the distribution of the three trajectories according to whether the firm experienced an HD in year *t* or not. The results shown in Table A.5 in the Online Appendix are in line with those shown in Table A.3. Second, we estimate an ordered logit model with interactions that relies on Eq. (5) using the matched sample. The results are shown in the third and fourth columns of Table 5. Overall, when we control for the likely endogeneity issue of the HD events, the results are in line with those shown in the first two columns of Table 5. Nonetheless, some interesting results emerge. First, our results confirm that HD events are not randomly distributed across firms. That is, the probability of experiencing an HD event is explained by/associated with firm-level characteristics, which is consistent with our findings in Table 2. Besides, high-decline events *per se* do not seem to have long-lasting effects on the growth and survival likelihoods. Second, when facing an HD event, some factors arise as very effective in improving firms' fates. On the one hand, while the level of productivity plays a positive role in the probability of taking a *fast growth* trajectory with respect to both *moderate positive or negative growth* and *exit from the market* when no HD event has occurred, its effect is smaller (because of a negative differential effect), conditional on the occurrence of an HD event. This result might indicate that while the level of productivity is key during "normal times", it may exacerbate rigidity in the aftermath of an HD event (Wiseman and Bromiley, 1996). On the other hand, among the other supply-side factors, while investments in both human capital and physical play a positive role in the probability of taking a *fast growth* trajectory, independent of whether or not the firm has experienced an HD event in *t*, the introduction of new processes is an effective strategy for achieving a positive growth trajectory, mostly after an HD event. If we consider the introduction of new processes as a proxy for productivity change, this result is somewhat in line with Dosi et al. (2015), who find that productivity change has a remarkable role in firm growth.

5 Further results

This section provides additional results that allow us both to assess the robustness of the main results and to add some insights for the interpretation of some key explanatory variables.

5.1 The role of small and young firms and the likelihood of HD

Given that small and young firms have higher growth rate variance (Axtell, 2018), the firms in the lowest decile are more likely to be small and young. Thus, we have repeated our analysis by splitting the sample into below-median and above-median size, and below-median and above-median age, to see if size or age are driving our results. The results are shown in Table 6. The first column reproduces the results of col. 1 of Table 2 to facilitate the comparison. Consistent with Table 2, although almost all determinants show the same sign for firms below and above the median size, the vast majority of statistically significant coefficients refer to the group of smaller firms (i.e., below-median size, col. 2). Thus, the

[20] See Caliendo and Kopeinig (2008) for a discussion of different matching algorithms.

probability of facing an HD event can be better explained in the group of smaller firms, where most of the HD events occur. Firms below and above the median age show similar coefficients for almost all determinants.

As for the role of structural characteristics, some noteworthy results stand out. First, firm age is negatively associated with the probability of facing an HD event for firms below the median size and age, while this result does not hold for larger and older firms. This result is coherent with the higher growth rate variance of young firms (Axtell, 2018). Second, firm size shows an asymmetric effect for firms below and above the median size. While size is positively associated with the probability of experiencing an HD event for below-median-sized firms, this association turns negative for firms that are above the median size. This is coherent with the results shown in cols. 2 and 3 of Table 2 which compares the role of firm size in HD events for SMEs and LEs and could suggest the existence of an inverted U-shaped relationship between firm size and the probability of HD, with the largest firms experiencing the lowest probability of fast decline. Overall, even if we recognize that the phenomenon under analysis is particularly relevant for micro and small firms, our main results seem to be not entirely driven by firm size and/or age. Nevertheless, digging deeper into the factors driving the difference in the results for below-median size and above-median size subsamples is beyond the scope of this paper; however, it merits further research.

5.2 Previous growth performance

A firm's past growth performance is important to better understand the likelihood of experiencing an HD event. Indeed, if the firm performed had high growth before the "fall", HD may be the result of a phase of internal reorganization after high growth. Conversely, if the previous growth performance was already disappointing, the consequences of facing an HD event could be much more stringent in terms of strategic and organizational difficulties. To further explore this issue, we re-estimate Eq. (1) by making use of more detailed information on the past growth performance of the firm. The results are shown in Table A.6, which includes the results of col. 1 of Table 2 in col. 1 for ease of comparison. In particular, we define three categories of past growth behavior of the firm before facing an HD event, namely, high-growth (HG, as defined in Table A.1), positive growth (all firms that experienced a positive growth rate below the 90^{th} percentile of the distribution in year *t-1* -omitted category-), negative growth (all firms that have experienced a negative growth rate in year *t-1*). Compared to positive past growth, we find a positive association between having experienced either HG or negative growth in *t-1* and the probability of an HD event in *t* (col. 2). The result is confirmed even if we replace negative growth with HD (collapsing all other past growth rates into the reference group). Thus, previous positive, but not extreme growth, leads to a fall in a firm's probability of facing HD. Overall, and in terms of the interpretation of the HD event, these results suggest that our definition of decline may comprise both cases in which the firm goes through an internal reorganization after high growth and cases in which the HD event is the result of a period of prolonged decline.

5.3 Growth trajectories after an HD event: definition and time horizon

We repeat the PSM analysis with two checks to assess the robustness of our PSM results reported in Table 5 of Section 4.3. First, we define *fast growth* as the trajectory followed from *t* to *t+3* by firms whose growth rates are above the 50th percentile (i.e., the median) in the distribution of three-year growth rates, rather than the 75^{th} percentile we previously used. Second, we compute the growth trajectories in the aftermath of an HD event from *t* to *t+5* (rather than the period *t* to *t+3*). The results displayed in Table A.7 are broadly consistent with those reported in Table 5.

6 Concluding remarks and implications for managers and policymakers

This study makes two main contributions. First, it contributes to the comprehension of the factors that precipitate a firm's sudden decline (Wiseman and Bromiley, 1996; Goedhuys and Sleuwaegen, 2016). In particular, the findings of the analysis of the occurrence of HD events both over the business cycle and across markets, combined with an overview of their determinants, can inform both managers and policymakers regarding the factors that cause a firm's

Table 6 Random effects logit model: What factors determine an HD event? Comparison of subsamples below and above median size and median age

	(1) All firms	(2) Below median size	(3) Above median size	(4) Below median age	(5) Above median age
PRODUCTIVITY	-0.0015*	-0.0037***	-0.0007	-0.0013	-0.0017**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
PROD_INN	-0.0791	-0.0499	-0.1149	-0.0398	-0.0983
	(0.087)	(0.136)	(0.120)	(0.124)	(0.120)
PROC_INN	-0.2618***	-0.3579***	-0.1551	-0.2717***	-0.2775***
	(0.071)	(0.103)	(0.103)	(0.097)	(0.102)
HUMAN_CAP	-0.2195***	-0.1871**	-0.1678	-0.2243**	-0.1802*
	(0.068)	(0.093)	(0.115)	(0.093)	(0.101)
PHYSICAL_CAP	-0.4122***	-0.4613***	-0.2089	-0.4850***	-0.3057***
	(0.069)	(0.078)	(0.166)	(0.086)	(0.117)
MARKETDYN_S	-0.4743***	-0.3330***	-0.6713***	-0.4258***	-0.5695***
	(0.073)	(0.101)	(0.116)	(0.099)	(0.110)
MARKETDYN_E	-0.6730***	-0.6391***	-0.7104***	-0.6653***	-0.6988***
	(0.112)	(0.166)	(0.158)	(0.148)	(0.168)
MARKETSH_S	-0.3136***	-0.3624***	-0.2804**	-0.2399**	-0.4116***
	(0.073)	(0.097)	(0.122)	(0.102)	(0.105)
MARKETSH_E	-0.5083***	-0.5717***	-0.4029**	-0.4506***	-0.5991***
	(0.109)	(0.154)	(0.163)	(0.148)	(0.165)
LEVERAGE	0.7572***	0.7173***	0.9080***	0.5569***	1.0217***
	(0.130)	(0.170)	(0.232)	(0.167)	(0.208)
HG	0.2131**	0.2268**	0.0917	0.2018*	0.1870
	(0.090)	(0.109)	(0.158)	(0.111)	(0.154)
PRICEVAR	-0.0154**	-0.0206*	-0.0121	-0.0150	-0.0134
	(0.008)	(0.011)	(0.011)	(0.011)	(0.011)
DIVERSI	0.1322	0.1101	0.1847	0.1688	0.1043
	(0.087)	(0.114)	(0.139)	(0.125)	(0.121)
AGE	-0.0044**	-0.0066**	-0.0015	-0.0139*	0.0021
	(0.002)	(0.003)	(0.002)	(0.007)	(0.002)
SIZE	-0.0163**	2.6429***	-0.0128**	-0.0193	-0.0175**
	(0.007)	(0.372)	(0.006)	(0.020)	(0.007)
FAMILY	-0.1333**	-0.1438	-0.2755**	-0.1029	-0.1800*
	(0.068)	(0.088)	(0.126)	(0.090)	(0.103)
Constant	-1.8923***	-1.9480***	-2.8519***	-1.690***	-2.1481***
	(0.258)	(0.326)	(0.444)	(0.394)	(0.364)
Ln of variance of the firm random effects	-0.5131***	-0.5131***	-0.3391**	-0.1554	-0.5968***
	(0.139)	(0.139)	(0.169)	(0.209)	(0.212)
Industry FEs (2-digit NACE rev.2)	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Observations	19,896	9,857	10,039	9,576	10,320

Firm-level clustered 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 sudden decline. Our results suggest that managers and entrepreneurs should pay special attention to the level of productivity, investments in physical and human capital as well as in new processes (as levers of productivity change), and they should maintain moderate financial leverage and balanced growth if they want to reduce the probability of facing an HD event. The results of this paper also stress the relevance of demand-side factors in explaining the probability of facing an HD event. Hence, strategies for enhancing a firm's idiosyncratic demand are essential. In this respect, policymakers may put into action some demand-side policies to sustain firms and prevent massive firm-size contractions in terms of employment (Nekarda and Ramey, 2011). Among other tools, governments may use public procurement, which refers to the purchase of goods and services from private companies by the public sector, to support SMEs, stimulating innovation and favoring a more efficient economy. This support is more easily implemented in the context of the stimulus packages that have been put in place in the context of the most recent crises (e.g., COVID-19 and energy crisis).

As for the structural characteristics of firms, policymakers should pay particular attention to young SMEs, which are more exposed than other firms to shocks that lead to wide "waves" of HD events, such as the Great Recession or the recent COVID-19 pandemic. Our results also show that higher levels of financial leverage are particularly detrimental in a downturn with respect to an upturn in the business cycle. Credit constraints seem more relevant than differences in productivity to explain differences in firms' probability of experiencing an HD event during a crisis, compared to their role during expansionary phases of the business cycle (Barlevy, 2003). This is coherent with the idea that, during a downturn, financial exposure plays an additional detrimental role in predicting abrupt decline events. In this respect, during a crisis, policymakers should ensure access to finance especially for young and small firms, which may find it more difficult to survive and might have positive effects on the whole economy in the long run (related to the so-called *scarring effects* of recessions; Ouyang, 2009). Young and small firms find it harder to refinance their long-term bank debt and have lower levels of equity capital with respect to their older and larger counterparts. Relying mostly on internal cash flow and commercial debt, young firms may face higher financial constraints, which hinder growth and favors decline (Cooley and Quadrini, 2004; Bottazzi et al., 2011).

Second, this work adds to the emerging literature on growth paths (McMahon, 2001; Garnsey and Heffernan, 2005; Garnsey et al., 2006; McKelvie and Wiklund, 2010; Coad et al., 2013) by examining firms' responses and their growth trajectories in the face of an HD event. Interestingly, we identify some choices that contribute to gaining stability or growth after an HD event. In particular, our findings indicate that several supply-side factors are relevant. More specifically, process innovation and investments in human capital increase the likelihood of embracing a positive growth trajectory when an HD event occurs. We also find that the dynamics of the firm's market share, as a proxy for the changes in a firm's idiosyncratic demand, are key to regaining a path of stability or growth if the firm has experienced an HD episode, and should lead the firm to put in action strategies for rebuilding a broad and solid customer base and enhancing a firm's reputation. Moreover, our findings suggest that other supply-side factors (e.g., investments in physical capital), and demand-side factors (the dynamics of the market in which a firm is active) contribute to the long-term growth of all firms (i.e., experiencing or not experiencing an HD). Our results also point out the relevance of the decisions taken by managers and entrepreneurs in the aftermath of an HD event. In particular, by investing in employees' skills and upgrading production processes, a firm may recover from an HD event. These results provide guidance in broadly determining the resources and strategic decisions that make a firm more resilient than others in facing adverse events.

Regarding the limitations of our study, while our dataset and methods allow us to provide a wide and thorough assessment of HD events, we cannot investigate the administrative and managerial changes that a firm in decline undergoes. Hence, in future research, qualitative and granular studies could be conducted to complement the insights provided by this work.

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